The Risks of Innovation: Are Innovating Firms Less Likely to Die?

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Abstract

While innovation is a source of competitiveness in the marketplace it may expose plants to survival risks. Using a rich set of data on Chilean manufacturing plants and their products we show that innovative multi-product plants have higher survival odds, a robust finding that is not driven by omitted variable biases or model specifications. Single-product innovators have lower chances of survival possibly because they are unable to hedge against risks. More generally, our results show that more 'cautious' innovators see their survival odds increase significantly while other types of innovators do not.

Keywords: Firm Exit, Firm Survival, Product Innovation, Multi-Product Firms, Chile.

JEL Classification codes: D24, L16, L6, O31.

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1. Introduction

Firm exit along with entry are crucial components of the evolution of industries both in developed and in developing countries (Caves, 1998, Tybout, 2000). Models of industry dynamics emphasizing producer heterogeneity and market selection such as Jovanovic (1982) and Ericson and Pakes (1989) suggest that in reasonably efficient markets 'superior' firms have higher chances to survive and grow. While being innovative is a central characteristic of 'superior' firms it also is a risky venture due to the uncertainties inherent to both the innovations themselves and their commercialization. The introduction of new products by a firm - an important type of innovation - involves high and often sunk development and production costs that may fail to bring a sufficiently high payoff to recover those costs.[1] Demand for these new products might not pick up or the products could be copied or replaced quickly by other new products developed by competitors. The model proposed by Ericson and Pakes (1995) illustrates the risks associated with innovation. In their model, firms engage in R&D investments which may improve their efficiency, profits, and survival but can also lead to firm exit if the outcome is not successful. Given that failed product launches are frequent, innovators may ultimately face a lower survival probability than other firms.[2] In this paper, we examine the relationship between product innovation and plant survival focusing specifically on the role of risk as a determinant of that relationship. We do so using a rich new dataset on Chilean manufacturing plants and all their products during the period 1996-2003.

Our paper makes several contributions to the empirical literature that studies the relationship between survival and observable producer characteristics, especially innovation-related variables,

[1] See OECD (2005) for a discussion of different types of innovation: product innovation, process innovation, managerial innovation, and organizational innovation.

[2] See Gourville (2006) on the failure of new product introductions. Famous examples of failed product launches include New Coke by Coca Cola and Sony's Betamax.

as a way to test the implications of industry dynamics models.[3] First, our dataset allows constructing an objective plant-level time-varying measure of product innovation based on the observation of whether a given product is newly manufactured by a plant in any year. This is a clear advantage relative to previous studies that use data from innovation surveys and rely on measures of innovation based on subjective perceptions of managers for a cross-section of firms.[4] Second, our measure captures product innovations that are new to a plant but not necessarily new to the country nor the world. While these types of innovation may be considered 'minor', their cumulative effects are important drivers of growth (Puga and Trefler, 2010). More importantly, in emerging market economies such as Chile 'minor' innovations account for the lion's share of innovation activities in contrast to path-breaking innovations associated with research and development (R&D) and patents that have been considered in previous studies of the innovation-survival link.[5] Third, our analysis goes beyond studying the simple link between innovation and firm survival by focusing on the role of risk as a crucial determinant of that link. Certain plants may engage in specific types of innovation that reduce their exposure to risk and may consequently benefit from higher survival odds. A particularly relevant dimension is the

[3] See Doms et al. (1995), Chen (2002), Disney et al. (2003), and Shiferaw (2009) for examples of studies of the determinants of firm survival and Manjon-Antolin and Arauzo-Carod (2008) for a review. For studies specifically examining the innovation-survival link see Esteve Perez et al. (2004), Hall (1987), and Cefis and Marsili (2006). Audretsch (1991) also examines the role of innovation-related variables for survival but by estimating the effects of industry-level innovation rates on industry-level survival rates, he leaves aside the heterogeneity in plant innovation decisions.

[4] In a review of existing innovation surveys Mairesse and Mohnen (2010) point to the problems with innovation measures that are subjective relying exclusively on perceptions by firms of whether they have introduced innovations at the process or product levels. They note that what is defined as a new or improved product is not always clear to the respondents and that the distinction between an innovation that is "new to the firm" and "new to the market" is also subject to a great deal of subjective judgment. Cefis and Marsili (2006) study the effect of innovation on firm survival relying on one such subjective measure of innovation (a dummy equal to one if a firm self-reports that it introduced either a product or process innovation during the sample period) for a cross-section of Dutch firms. Their overly encompassing definition of innovation has the shortcoming (acknowledged by the authors) of potentially underestimating the effects of innovation on survival.

[5] Esteve Perez et al. (2004) and Hall (1987) show a positive impact of R&D activities on the survival of firms in Spain and the U.S., respectively.

distinction between single-product and multi-product plants.[6] If a single-product plant introduces one new product that replaces the previous product it manufactured (thus remaining a single-product plant) its only source of revenue is put at stake as the market may not take up the new product, while that is clearly not the case for a multi-product plant that introduces a new product while retaining other more established sources of revenue. Hence, we examine the differences in the innovation-survival link across multi-product plants and single-product plants. We also explore an application of the risk-minimizing diversification principles from the finance literature to innovation. The basic hypothesis that we consider is the possibility of 'cautious' innovations by plants, i.e., the addition of products to an existing product range rather than the switch into an entirely new product range, or the introduction of new products on a small scale that may reduce risk and uncertainty associated with innovation and thus be linked to higher survival odds. We also consider the differences in the innovation-survival link over an economic crisis during our sample period as another way to test the importance of risk. Fourth, we conduct a more rigorous test of the innovation-survival link than was done in previous studies by using as our main econometric specification a Cox proportional hazard model of plant survival and by applying a large set of tests to probe the validity of our results. Our rich plant-level panel dataset allows us to correct for possible omitted variable biases. In addition, we consider different models including a linear probability model which we estimate by plant fixed effects instrumental variables as well as models using the Weibull and conditional log-log distributions to account for unobserved heterogeneity. Finally, we should note that to the best of our knowledge, ours is the first study to examine the innovation-survival link in the context of an emerging economy.

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[6] An emerging literature shows the importance of considering the specificities of multi-product plants in studies of industry dynamics as well as in studies of plant-level responses to trade liberalization (Bernard et al., 2010).

Our main findings suggest that product innovation is beneficial for the survival of Chilean multi-product plants and of plants engaging in 'cautious' innovations but it is not beneficial for survival of single-product innovating plants nor for plants engaged in risky product innovations. Our main results are obtained by estimating a Cox proportional hazard model controlling for multiple plant characteristics as well as industry, year, and region fixed effects. Our findings are robust to multiple checks of the model's assumptions namely the proportionality assumption and the potential for distinct effects across plant ages and for plants belonging to multi-plant firms. Moreover, our results hold using a variety of alternative specifications. In conformity with the literature, we find a positive relationship between size, age, and productivity and the probability of survival of Chilean manufacturing plants.[7]

The relationship between innovation and plant survival is important for policy across several dimensions. Plant exit is a major cause of unemployment; therefore, our findings are important for implicitly assessing the employment-innovation link. The implications of our findings are manifold. First, while our evidence suggests that plants may have incentives to engage in more cautious types of innovation, those may not be feasible for all plants in all types of industries. For example, small plants may be unable to engage in 'cautious' innovations since they lack the capacity to maintain a large product range. Also, products for which a radical switch in production is required for innovation, the introduction of new products can occur only on a large scale. Hence, there could be a role for public policy in promoting investments that potentially result in cautious innovations for certain types of plants as well as in providing some guarantees or help to deal with failed innovations. Obviously, such policy interventions would need to be

[7] Bernard and Jensen (2007), Disney et al. (2003), Dunne et al. (1989), Hopenhayn (1992), and Jovanovic (1982) are some of the theoretical and empirical studies showing that size, age, and productivity are negatively correlated with firm exit.

designed so as to set the right incentives ensuring that no moral hazard problems arise. Note that the negative effects of innovation on the survival of plants that are single-plant firms do not necessarily suggest negative effects for the industry or economy at large as ideas might be taken up by larger multi-plant firms. It is, however, a powerful explanation why such plants often do not get involved in innovative activities. A negative policy implication that does arise from our findings is that there are cases where innovative activities affect employment negatively, namely when non-cautious types of innovations lead to plant exit. Such developments will not necessarily present a challenge as long as plants' resources (particularly their workers) are quickly and efficiently redeployed. Therefore, policies to support new start-ups and innovative young firms are particularly important, as stressed in OECD's recent *Innovation Strategy* (OECD, 2010).

The paper is organized as follows. We describe the data in Section 2. Section 3 proposes the regression framework. Our main results are discussed in Sections 4 and 5 and Section 6 concludes.

2. Data

We make use of a unique dataset on Chilean manufacturing plants and their products (ENIA) collected by the Chilean Statistical Institute (INE) and spanning the 1996-2003 period. The fact that the ENIA is a census of Chilean plants with more than 10 employees is crucial for our analysis of plant survival.[8] The unique identifier included in the ENIA allows us to follow plants over time and identify exit of plant A in year *t+1* if plant A belongs to the ENIA in year *t* but

[8] Details on the manufacturing firm census (ENIA) are provided in Paunov and Fernandes (2008). Note that the fact that the ENIA includes only plants with more than 10 employees poses a potential problem in that plants might drop out of the dataset if their employment falls below that number. We address this problem in column (2) of Table 5.

does not belong to the ENIA in year *t+1* (nor thereafter). Plant survival in the ENIA was previously studied by Alvarez and Vergara (2008) and Lopez (2006) who linked it to policy reforms and to the use of imported inputs. Another important advantage of our data is that we can identify multi-plant firms.[9] Disney et al. (2003) point to the importance of accounting for this dimension as there can be significant differences across single-plant and multi-plant firms in terms of survival.

The crucial feature of our dataset is that it provides for each plant and year information on the entire set of products manufactured and sold classified at the 7-digit ISIC level (revision 2).[10] Our main measure of product innovation is a dummy variable that equals one for a plant in year *t* if the plant sells one or more new 7-digit products, where a new product is a product that the plant has never sold prior to year *t-1*. Note that our definition of innovation considers a product to be new if it is new for the plant even if it is not new to the market or the world.

In the Chilean manufacturing sector, the average yearly exit rate is above 9% during the sample period. Exit rates - shown in Table 1 - differ somewhat across industries ranging from a low rate of 6% in the basic metals industry to rates above 11% in textile, wearing apparel and leather, wood and wood products. Across the sample about 8% of plants are part of a multi-plant firm. Multi-plant firms are particularly important in the non-metallic minerals and the basic metals industries. In the full sample, about 51% of plants produce multiple 7-digit ISIC products and in any given industry more than 43% of plants produce more than one product. With regard

[9] The Chilean Statistical Institute (INE) collects information on which plants in the ENIA survey are part of a multi-plant firm i.e., a firm with at least two plants responding to the survey. The information was kindly provided to the authors for the purposes of this research project. During the 1997-2003 sample period on average 8.3% of firms are multi-plant firms. In the rest of the paper we will be particularly careful to denote single-unit establishments which are the object of ENIA's survey as 'plants' and refer to 'firms' only when this corresponds to units with multiple plants.

[10] See Navarro (2008) for descriptive statistics and Fernandes and Paunov (2009) for additional details on the products data. Since there was a change in the product classification from the ISIC Rev. 2 classification to the ISIC Rev. 3 classification in 2001, we omit that year in the econometric analysis.

to innovation, Table 2 shows that the average percentage of plants introducing new products at the 7-digit ISIC level is 13.4%. The innovation rate is lowest for the food, beverage and tobacco industries - where only about 8% of plants innovate - and well-above average for a set of diverse industries from textiles, wearing apparel and leather, wood and wood products to chemicals, basic metals and fabricated metal products industries.

Next, we define alternative measures of innovation, splitting plants into categories that may suggest more or less cautious types of innovation. First, we distinguish across multi-product and single-product plants. Second, we identify plants who innovate without dropping previous products separately from those who innovate but drop products at the same time. Third, we consider separately plants that introduce new products that account for more than 50% of revenues and plants whose new products account for less than 50% of revenues. Fourth, we consider plants who introduce a new product in a new industry where they did not produce before versus plants that introduce new products in a known industry. On average, we find that for all measures innovation occurs mostly under a more cautious setting.[11]

In the Chilean dataset we observe that plants that are successful in introducing one or more new products do not necessarily remain successful in the marketplace and some exit. To obtain some preliminary insight into the univariate relationship between plant survival and innovation (i.e., ignoring the role of covariates) we show in Figure 1 the Kaplan-Meier survival functions for plants that engage in product innovation and for plants that do not.[12] Innovative plants are

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[11] Note that our innovation indicators are sensible, we find a positive significant relationship between innovation and labor productivity as well as exporting in simple regressions including industry and year controls.

[12] The Kaplan-Meier function provides an estimator for the survivor function that is the probability of survival up to period *t* and after and is obtained as $\hat{S}(t_i) = \prod_{i=1}^{j} (n_i - h_i) / n_i$ where *n* is the population alive in t_i and *h* is the number of failures in t_i (Kiefer, 1988).

more likely to survive than plants that do not innovate: after five years, 71% of the innovating plants survive while only 55% of non-innovating plants survive.

3. Model Specification

To identify more rigorously the effects of innovation (and other plant characteristics) on plant survival, we follow the empirical literature in considering a 'hazard' model to estimate the probability that a plant with characteristics X exits the market at t conditional on having survived until t (Manjon-Antolin and Arauzo-Carod, 2008). The use of a 'hazard' model is adequate due to the incomplete nature of the duration information: observations of plants still in operation at the end of the sample period are right-censored. This implies that the use of conventional estimation methods such as OLS would provide biased results whereas 'hazard' models have been specifically designed to tackle the problem of right-censoring of observations. In the analysis of plant survival, the dependent variable of interest is the time/spell between plant entry and exit and the key idea is that the length of this survival spell is the realization of a random variable T. The probability of a plant ending a survival spell for an infinitesimally small time interval after t is known as the 'hazard' function.[13] Since the shape of the hazard functions for survival is unknown, certain assumptions need to be made. The conditional hazard function is defined as the conditional density of T given that $T > t$ and X: $\lambda(\tau, X) = f(\tau / \tau > t, X) = f(\tau / X)/(1 - F(\tau / X))$ and the hazard rate is the value of this function at particular τ and X. Following the literature on firm survival (e.g., Audretsch and Mahmood, 1995; Agarwal and Audretsch, 2001; Chen, 2002; Disney et al., 2003; Girma et al.,

[13] In other words, the hazard rate is the probability that a plant will experience an event (exit) at time t, while the plant is at risk for having an event (the plant survived until $t-1$). The hazard rate is the unobserved rate at which events occur.

2006) we consider a proportional hazard model with $\lambda(\tau, X) = \lambda_0(\tau) * \phi(X)$, where $\lambda_0(.)$ is a baseline hazard that depends only on time duration and can be interpreted as the hazard function for the mean plant in the sample and regressors *X* multiply the hazard function by a scale factor $\phi(.)$. Our main specifications assume an exponential functional form for $\phi(.)$, $\phi(X) = e^{X\beta}$, whereby the proportional effect of *X* on the conditional probability of ending a survival spell does not depend on time duration following Cox (1972). In other words, the proportional hazard model assumes that the impact of any factor on a plant's survival probability is the same independently of plant age.[14] This assumption is somewhat restrictive and is investigated in Section 4. The Cox semi-parametric partial likelihood method that we use allows one to recover estimates of β without making any assumptions on the distribution of the baseline hazard function.[15] Our empirical specification is given by the conditional hazard function:

$$\lambda_i^1(t) = \lambda_0(t) e^{(\beta Innovation_{it} + \gamma X_{it} + I_t + I_r + I_j)} \tag{1}$$

where $\lambda_i^1(t)$ is the rate at which plants exit at time *t* given that they have survived in *t-1*, $\lambda_0(t)$ is the baseline hazard function (which provides the value of the conditional hazard function when all regressors are zero), *Innovation* is our main measure of product innovation defined in Section 2 and *X* is a vector of controls for plant *i* in year *t*. The variables I_t, I_j, and I_r are year, 4-digit ISIC industry, and region fixed effects, respectively. In order to explore potential differences across multi- and single-product plants we estimate the following conditional hazard function:

[14] In principle the use of the Cox proportional hazard model would require survival time to be a continuous variable and plants to be ordered exactly regarding their failure time. However, survival time in our dataset is discrete and while we know which plants and how many plants exit from year to year, we are unable to order plants' failure times within a year, i.e., there are 'ties' among plants. Our estimations in Section 4 make use of the method of Breslow (1974) to correct the Cox partial likelihood function for the existence of 'ties'.

[15] Additional details on hazard functions are provided in Kiefer (1988), Klein and Moeschberger (1997), and Hosmer and Lemeshow (2008).

$$\lambda_i^{\,2}(t) = \lambda_0(t) e^{(\beta^1 Innovation_{it} * Multi + \beta^2 Innovation_{it} * Single + \gamma X_{it} + I_t + I_r + I_j)} \qquad (2)$$

where the innovation measure enters interacted with a dummy variable identifying multi-product plants and interacted with a dummy variable identifying single-product plants and the rest of the variables are defined as above. An important concern that arises for the survival specifications in equations (1) and (2) is that product innovation is a choice variable for the plant which is very likely correlated with the unobservables determining also survival. For example the introduction of new products depends on managerial ability which also plays a critical role for plant survival. To address this potential omitted variables problem our econometric specifications control for several plant characteristics. We account for plant productivity which is an important theoretical and empirical determinant of plant survival in itself, but also since it can be a proxy for other unobservable and desirable characteristics of plants that may be linked to survival (Shiferaw, 2009). We use labor productivity instead of TFP due to the difficulties for inference that would arise from including an estimated TFP variable in our regression framework.[16] Following the literature on plant survival, we also control for age, size, and capital intensity as well as an indicator for multi-plant firms following Dunne et al. (1989), Disney et al. (2003), and Bernard and Jensen (2007).[17] By controlling for capital intensity we ensure that our product innovation coefficient is not picking up the effect of capital accumulation through process innovation. To assess the significance of the estimated coefficients we use robust standard errors that are clustered by plant to account for repeated observations on plants.

[16] Moreover, by using labor productivity we avoid the problems that are associated with the measurement of TFP for multi-product plants highlighted by Bernard et al. (2009).
[17] The definitions of the plant characteristics used in the specifications are provided in the Appendix.

4. Results

4.1 Main Results

We start by estimating equation (1) to explore the relationship between plant survival and innovation for comparability with previous studies. Column (1) of Table 3 shows the results from a simpler variant of equation (1) that includes innovation and only year, industry, and region fixed effects. Column (2) adds the indicator for multi-plant firms, column (3) adds plant size and capital intensity, and column (4) adds labor productivity. The coefficients from the Cox model shown in Table 3 (as in all other tables) measure semi-elasticities of the hazard rate with respect to each regressor (i.e., the regressors enter linearly into the log of the conditional hazard function and therefore multiply the baseline hazard by a factor that is independent of duration). Columns (1)-(4) show that product innovation has a positive effect on plant survival in Chile. [18] Additionally the estimates show that multi-plant firms are much more likely to survive than single-plant firms, and large plants and plants with higher capital intensity have higher survival probabilities. The chi-squared likelihood ratio tests for the Cox models in Table 3, as well as in other tables, shows that the determinants of survival considered are jointly significant.

The Cox specification assumption that the impact of any factor on plant survival probability is the same independently of plant age may be too restrictive. Hence, we test for the proportionality assumption using the Schoenfeld and scaled Schoenfeld residuals as suggested by Hosmer et al. (2008). Based on the test, we cannot reject the proportionality assumption for product innovation but we reject it for capital intensity, labor productivity, and the multi-plant indicator. Hence, we report in column (5) of Table 3 the results from re-estimating equation (1)

[18] Note that the coefficient on product innovation can be interpreted as the constant proportional effect of product innovation on the conditional probability of completing a survival spell. Hence a negative coefficient implies that product innovation is associated with a lower hazard or equivalently a higher survival probability.

interacting each of these three variables with plant age. All results are qualitatively maintained. Interestingly, we find that being part of a multi-plant firm is more important for survival in the early stages of a plant's life. In column (6) we test whether allowing the effects of innovation to differ for multi-plant firms versus single-plant firms separately matters. The t-test shows that the effect of innovation on survival differs significantly across these two types of plants only at larger than 10% confidence level.

Overall our estimates show that innovation has a positive and significant effect on plant survival. The coefficient in column (4) of Table 3 suggests that a plant's decision to engage in product innovation would decrease its probability of death by 14%, keeping all other variables constant.[19] Our evidence is in line with the findings by Cefis and Marsili (2006) based on perception-based innovation measures from the Community Innovation Surveys and by Esteve Perez et al. (2004) and Hall (1987) based on R&D activities.

Next, we estimate equation (2) to examine the differential effects of innovation on plant survival for multi-product plants relative to single-product plants. Column (1) of Table 4 reports the results from estimating a simpler variant of equation (2) that includes only the product innovation variable for multi-product plants and for single-product plants, along with an indicator for multi-product plants. The estimates suggest that multi-product plants are more likely to survive and that it is the multi-product innovators that mostly benefit while single-product innovators seem by contrast to be at a higher risk of exit because of their innovative behavior. Progressively adding plant controls in columns (2) to (4) of Table 4 as in Table 3, we find that these findings are maintained. The test for the proportionality assumption again shows that it is rejected for capital intensity, labor productivity, and the multi-plant indicator. Thus, column (5)

[19] This magnitude is obtained as 1- exp (-0.151).

presents the results from re-estimating equation (2) interacting each of these three variables with plant age. The main findings are still that multi-product innovators are more likely to survive than single-product innovators.

The coefficients in column (4) of Table 4 suggest that, relative to non-innovating plants, the probability of death is decreased by 18% for innovative multi-product plants while it is higher by 21% for innovative single-product plants.

4.2. Robustness

In this section we address several concerns about the validity and strength of our results and present the estimates in Table 5. First, we re-estimate equation (2) for single-plant units only (i.e., where plants equal firms) to avoid possible problems related to this source of heterogeneity across plants. This specification allows us to see whether the effects of innovation also hold for firm rather than plant survival. Column (1) shows that this is indeed the case.

Second, the ENIA collects information only for plants with more than 10 employees. Hence, exit could be mechanically due to the fact that a plant reduces its workforce below 10 employees. We address that question by re-estimating equation (2) for the sub-sample of plants with more than 15 employees.[20] Column (2) shows that this concern is not warranted as the findings are qualitatively maintained for that sub-sample of plants.

Third, we modify our measure of innovation to be more aggregate capturing products introduced at the 6-digit ISIC rather than the 7-digit ISIC level. The corresponding results in column (3) are qualitatively similar to those in Table 4. Moreover, unreported results show that the evidence is upheld for new products introduced at the 5-digit ISIC level.

[20] We exclude from this sub-sample all observations of a plant if the plant reports having less than 15 employees in any of the sample years.

Fourth, we add to our specification several time-varying industry characteristics that might affect survival and alter the innovation-survival: sales growth, the Herfindahl index of concentration, and a measure of innovation all at the 4-digit ISIC level following Audretsch and Mahmood (1995), Audretsch (1995), Mata and Portugal (1994), Strotmann (2007) among many others. Column (4) shows that the link between innovation and plant survival is maintained. However, it also shows that surprisingly none of these factors affects plant survival significantly. A possible theoretical explanation for this lack of significance is that industry dynamics have ambiguous effects on survival. On the one hand, fast growing industries afford higher survival possibilities as growth of some plants does not necessarily result in market share losses of rivals, and hence may lead to fewer aggressive reactions by the latter. On the other hand, in fast growing industries conditions are more unsettled and higher turnover rates might result. Another explanation for this lack of significance is the inclusion of 4-digit industry fixed effects which capture time-invariant industry characteristics. In unreported regressions where we include the industry characteristics but exclude industry fixed effects we find a negative and significant effect of industry average innovation on plant survival. Our finding of lower survival odds in highly innovative environments is similar to the findings by Audretsch (1995) and Audretsch and Mahmood (1995) for U.S. firms.

Fifth, we add to our specification several plant characteristics (not considered before for parsimony): the square of plant size, initial plant size following Disney et al. (2003), and indicators of whether plants are exporters or foreign-owned. The estimates reported in column (5) confirm our findings and suggest a non-linear relationship between plant size and survival as reported in the literature. The results also suggest that initial plant size is inversely related to survival.[21] Exporting and foreign-ownership status have no significant impact on plant survival once all other covariates are controlled for.

Sixth, our estimates so far restrict the baseline hazard function to be similar across all observations. Baseline hazards may, however, vary across industries or across years. To examine whether this restriction affects our results we allow the baseline hazard function to differ across 4-digit ISIC industries or across years while assuming that the coefficients on the regressors are similar across these different strata. The results reported in columns (6) and (7) show that our findings are robust to the consideration of differential baseline hazard functions.

Seventh, we examine whether the results are robust to the use of models other than the Cox proportional hazard for the hazard rate and for plant exit probabilities. We start by estimating the effects of innovation on plant exit using a linear probability model and find qualitatively similar results in column (8). An advantage of this set-up is that we can implement a more demanding identification strategy for the effect of innovation. Favorable plant shocks or unobservable plant characteristics may lead plants to innovate and remain in business, resulting in a potential positive bias in the effect of innovation. To address this bias we follow a plant fixed effects instrumental variable (IV) approach. As an emerging economy, Chile is mostly an adopter and adapter of knowledge generated abroad. Hence, it makes sense to consider as an instrument a variable that captures technological progress at the knowledge frontier as this is likely to generate more innovation opportunities for plants in Chile while it should not impact those plants' exit decisions through any other channel. Thus the first instrument we consider is the number of patents in the plant's 2-digit ISIC industry in the United States. Access to foreign knowledge by

[21] While the dataset used for our analysis that includes information on plants' 7-digit products begins in 1996, we have access to information on all plants since their entry into the ENIA from 1979 onwards. We use this information to compute plant age (as mentioned in the Appendix) as well as initial plant size, which is the number of employees that the plant report in its first year in the ENIA since 1979.

Chilean plants should be facilitated by the investment capacity of the plant's industry through spillover mechanisms. Hence, the other instrumental variable we consider is the investment-capital ratio in each of Chile's 4-digit industries. These industry-level variables should not be correlated with plant exit other than through plant innovation decisions.[22] The results from IV-2SLS estimation are reported in column (9).[23] Note that this specification includes only the innovation variables of interest. It excludes all other plant control variables to avoid their use as instruments.[24] We find the effects of innovation on plant survival to be qualitatively maintained.

Finally, we conduct a specification test by estimating parametric regression survival models using full maximum likelihood. We consider two specific parametric forms for the distribution of the baseline hazard function: Weibull and log-logistic.[25] Columns (10) and (12) present the corresponding estimates and show that the results are qualitatively maintained. An advantage of using the Weibull and log-logistic parametric survival models is that they allow us to explore the relevance of heterogeneity as plants may still have differing duration distributions even after controlling for a rich set of plant characteristics. The presence of such unobserved heterogeneity could lead to misleading inferences about the effects of our key regressors of interest, the innovation measures. To address this possibility we re-estimate the parametric models as 'frailty' models allowing for unobserved heterogeneity.[26] The corresponding estimates are presented in

[22] Appendix Table 1 provides details on how each of the instrumental variables is defined.
[23] The first stage results show that the number of patents and the investment capacity of industries are positively and significantly correlated with innovation. These estimates are available from the authors upon request.
[24] Instruments are interacted with the multi-product indicator and the single-product indicator.
[25] In this case, in addition to the coefficients on the regressors, the parameter of this distribution is also estimated (though the corresponding estimates are not reported in Table 5). In general, the Weibull distribution is indicated for data with monotone hazard rates, that increase or decrease exponentially over time, while the log-logistic distribution is indicated for data with non-monotonic hazard rates, initially increasing and then decreasing. A stylized fact from the literature on plant survival (Caves, 1998) is that hazard rates tend to increase upon plant entry and then decrease as plants age. This might suggest that the log-logistic model might be more appropriate, however Weibull models have been used in several studies on firm survival (Manjon-Antolin and Arauzo-Carod, 2008).
[26] We consider mixture models where the hazard function is multiplied by a plant-specific random variable that is assumed to follow a gamma distribution in column (11) and a normal distribution in column (13).

columns (11) and (13) and show that the effects of innovation by multi-product plants and by single-product plants on survival are qualitatively similar to those in specifications that do not account for heterogeneity.

5. The Potential Effects of Risk

Our robust finding in Tables 4 and 5 of positive significant effects of innovation merely concentrated among multi-product plants is surprising. One of the most tempting rationales for why one would find negative effects of innovation on the survival of any plant (in our case, the single-product plants) seems to be the risk involved in the introduction of new products to the market. We examine this question in depth by exploring three different types of risks and their relevance for the effects of innovation on survival. First, the risk of introducing a new product would be significantly higher if the importance of that product in a plant's overall revenues is substantial. A more cautious approach for a plant would consist in introducing a new product on a 'small scale' i.e., such that it would represent a relatively small share of plant overall revenues. We re-estimate equation (1) including an indicator that identifies the more 'cautious' innovators - i.e., plants that introduced new products accounting for less than 50% of revenues - and an indicator that identifies the other less 'cautious' innovators. The corresponding results reported in column (1) of Table 6 show a positive and significant effect of innovation on plant survival only for the more cautious approach.

Second, the risks of engaging in product innovation are likely to be lower if a plant introduces new products while still manufacturing old products as opposed to introducing new products but dropping old products. The former type of innovation might be labeled more cautious innovation. Column (2) shows the results from re-estimating equation (1) including indicators for the two types of innovation. The results are striking: innovation is beneficial for plant survival only for cautious innovators that manage to diversify away the risks. The p-value shows that the difference in coefficients across cautious and non-cautious innovation is statistically significant at the 1% confidence level. Non-cautious innovators may derive some benefits from innovation but risks and benefits outbalance one another so that on average their survival probabilities are actually worse than those of non-innovators.

Third, a plant may undertake a more risky innovation strategy if it ventures into product innovation in a completely new industry relative to doing it in a known industry. The rationales are intuitive: plants are likely to have less technical and market knowledge in a completely new industry. Column (3) shows the results from re-estimating equation (1) considering separately product innovation in a 4-digit industry where the plant has already manufactured other products and innovation in an entirely new 4-digit industry for the plant. Both types of innovation are associated with higher survival odds but only innovation in an old 4-digit industry has a statistically significant effect. This result suggests that the risk associated with venturing into a new industry does affect the trade-off between innovation and survival. To consider a potentially larger risk, we show the results in column (4) for a specification where we consider innovation in a new 3-digit industry versus innovation in an old 3-digit industry. The findings are qualitatively maintained, i.e., more cautious types of innovation in an old 3-digit industry increase plant survival odds significantly while that is not the case for more risky ventures of manufacturing products in new 3-digit industries.

Finally we consider a different perspective on the role of risk for the link between innovation and survival by exploiting the existence of a crisis in Chile during our sample period.[27] Crisis periods would tend to have the following effects: an increase in exit rates (Salvanes and Tveteras, 2004) and a reduction in innovation rates (OECD, 2009; Paunov, 2010).[28] This reduction may partly be due to the fact that in crisis periods the success of new products may be reduced as competition becomes fiercer and consumer demand may be directed at standard rather than novel products. We explore whether the beneficial effects of innovation on survival for multi-product plants identified in Tables 4 and 5 are different in crisis relative to growth periods. We re-estimate a version of equation (2) where we interact our innovation variables with a dummy identifying years 1998 and 1999 which constituted a crisis period for the Chilean economy. The results reported in column (5) of Table 6 show that the impact of innovation on plant survival is not significantly different in crisis relative to growth periods. This finding suggests that from the perspective of guaranteeing survival, plants have no incentive to change their innovation strategy in a crisis period. Lower innovation rates during crisis periods must therefore be due by other factors such as the difficult access to financial resources but not to a preoccupation of plants regarding lower returns from innovation in terms of survival.

5. Conclusion

Innovation is not only potentially very costly but can also expose plants to significant survival risks as the launch of new products may result in lower than expected sales. At the same time, innovation is a potentially powerful source to allow plant survival in the marketplace. This paper shows that innovation helps to reduce the probability of plant exit under certain circumstances. Chilean multi-product plants and plants involved in risk-mitigating product

[27] See Valdez (2009) for a description of the crisis in Chile.

[28] The two studies document the effects of the financial crisis of 2008-2009 on innovation across OECD economies (OECD, 2010) and on firms' innovation investments across eight Latin American economies (Paunov, 2010).

innovations indeed see beneficial effects. However, single-product plants and plants engaged in risky product innovations are at greater risk of exiting than non-innovating plants.

Our findings have different policy implications. First, our results show that while there are positive micro-level effects of innovation on the survival of some manufacturing plants, these do not hold for plants engaging in non-cautious types of innovation. This suggests an additional reason for underinvestment in innovations from the point of view of the plant beyond the usual fears of not appropriating all the benefits from innovation. Second, while cautious innovation is the most desirable innovation strategy to obtain a survival payoff, it may not be feasible for all types of plants nor in all types of industries. Policy actions may be required to improve for example the capacity of small plants to engage in cautious innovation given the desirability of small plant survival in terms of securing employment. Where risky innovation is the only possibility, an adequate policy mechanism that avoids moral hazard problems would be required that provides a guarantee to help failed innovation while setting the right incentives.

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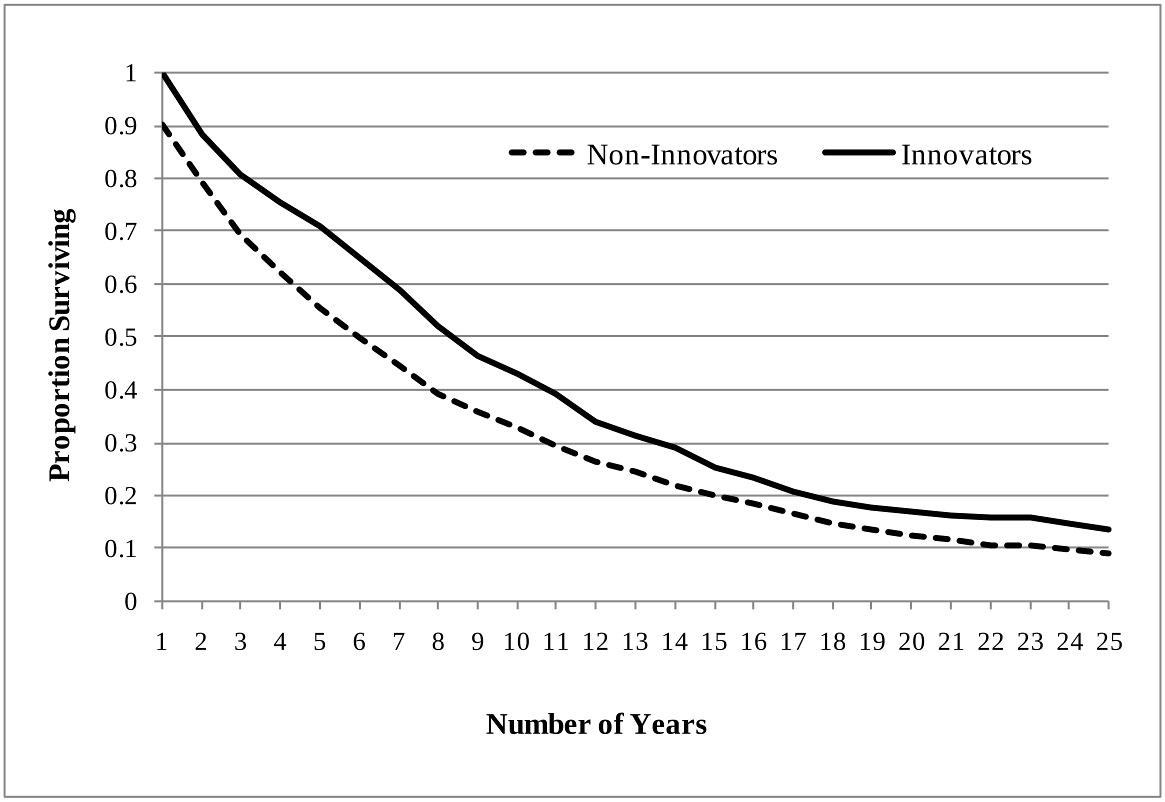
Figure 1: Kaplan-Meier Survival Estimates



Notes: the number of years in the X-axis designates age categories: our sample includes plants that range in age from 1 to 25 years old (where age is measured relative to 1979). The graph assesses for each age category what is the probability of survival for innovators and for non-innovators.

Table 1: Descriptive Statistics on Exit, Multi-Plant Firms, and Multi-Product Plants

	Exit Rate	Percentage of Multi-Plant Firms	Percentage of Multi-Product Plants
Full Sample	9.4%	8.3%	51.0%
Food, Beverages and Tobacco (ISIC 31)	8.8%	11.5%	50.3%
Textile, Wearing Apparel and Leather Industries (ISIC 32)	11.5%	2.1%	54.7%
Wood and Wood Products, Including Furniture (ISIC 33)	11.9%	5.8%	55.5%
Paper and Paper Products, Printing and Publishing (ISIC 34)	7.7%	5.4%	43.4%
Chemicals and Chemical, Petroleum, Coal, Rubber and Plastic Products (ISIC 35)	7.3%	11.8%	54.7%
Non-Metallic Mineral Products,except Products of Petroleum and Coal (ISIC 36)	10.8%	26.3%	44.9%
Basic Metal Industries (ISIC 37)	6.0%	16.2%	47.7%
Fabricated Metal Products, Machinery and Equipment (ISIC 38)	9.4%	3.5%	48.6%
Other Manufacturing Industries (ISIC 39)	9.2%	2.3%	49.3%

Note: For full sample and for each 2-digit industry, the numbers in the table are averages calculated across all years.

Table 2: Descriptive Statistics on Innovation

	Product Innovation	Product Innovation by Multi-Product Plants	Product Innovation by Single Product Plants	Product Innovation without Product Dropping	Product Innovation with Product Dropping	Product Innovation Less than 50% of Revenues	Product Innovation More than 50% of Revenues	Product Innovation in 'Old' Industry (4-Digit ISIC)	Product Innovation in 'New' Industry (4-Digit ISIC)	Product Innovation in 'Old' Industry (3-Digit ISIC)	Product Innovation in 'New' Industry (3-Digit ISIC)
Full Sample	13.4%	11.6%	1.8%	7.0%	6.4%	9.6%	3.8%	7.2%	6.0%	8.7%	4.5%
Food, Beverages and Tobacco (ISIC 31)	8.3%	7.9%	0.4%	2.8%	5.5%	7.0%	1.3%	6.0%	2.3%	6.9%	1.3%
Textile, Wearing Apparel and Leather Industries (ISIC 32)	14.5%	12.8%	1.7%	8.7%	5.8%	10.9%	3.6%	8.2%	6.2%	9.2%	5.1%
Wood and Wood Products, Including Furniture (ISIC 33)	20.3%	16.7%	3.7%	11.6%	8.7%	12.6%	7.8%	14.4%	5.7%	15.2%	5.0%
Paper and Paper Products, Printing and Publishing (ISIC 34)	12.2%	10.3%	1.9%	5.6%	6.6%	8.3%	3.9%	5.9%	6.3%	7.7%	4.4%
Chemicals and Chemical, Petroleum, Coal, Rubber and Plastic Products (ISIC 35)	15.0%	13.2%	1.9%	8.5%	6.5%	11.1%	4.0%	7.5%	7.5%	8.8%	6.2%
Non-Metallic Mineral Products,except Products of Petroleum and Coal (ISIC 36)	10.8%	8.5%	2.3%	5.3%	5.5%	5.7%	5.2%	7.1%	3.7%	8.1%	2.7%
Basic Metal Industries (ISIC 37)	20.6%	14.3%	6.2%	11.2%	9.4%	10.7%	9.9%	8.7%	11.7%	11.2%	9.2%
Fabricated Metal Products, Machinery and Equipment (ISIC 38)	16.5%	13.8%	2.7%	9.8%	6.7%	11.3%	5.2%	5.1%	11.0%	8.1%	8.0%
Other Manufacturing Industries (ISIC 39)	14.6%	13.7%	0.9%	6.6%	8.0%	13.0%	1.6%	5.0%	9.3%	6.5%	7.9%

Note: For full sample and for each 2-digit industry, the numbers in the table are averages calculated across all years.

Table 3: Initial Results

	Cox Proportional Hazard Regression					
	(1)	(2)	(3)	(4)	(5)	(6)
Product Innovation	-0.152**	-0.158**	-0.143**	-0.153**	-0.151**	
	(0.065)	(0.065)	(0.066)	(0.067)	(0.067)	
Product Innovation * Multi-Plant Firm						-1.786*
						(1.019)
Product Innovation * Single-Plant						-0.135**
						(0.068)
Multi-Plant Firms		-0.925***	-0.786***	-0.834***	-2.522***	-0.758***
		(0.127)	(0.133)	(0.153)	(0.695)	(0.154)
Multi-Plant Firms * Age					0.673***	
					(0.255)	
Size			-0.223***	-0.170***	-0.171***	-0.169***
			(0.028)	(0.030)	(0.030)	(0.030)
Capital Intensity			-0.041**	-0.0002	-0.122***	0.0001
			(0.019)	(0.022)	(0.044)	(0.022)
Capital Intensity * Age					0.060***	
					(0.020)	
Labor Productivity				-0.214***	-0.019	-0.215***
				(0.036)	(0.078)	(0.036)
Labor Productivity * Age					-0.092***	
					(0.034)	
P-Value for Difference in Product Innovation Coefficients						0.11
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
4-Digit Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21381	21381	21283	20497	20497	20497

Notes: Robust standard errors clustered at the plant level in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% confidence levels, respectively. The table shows coefficients from the Cox proportional hazard regression model. The p-value shown at the bottom of column (6) tests the null hypothesis that the difference in coefficients on product innovation for multi-plant firms and on product innovation for single-plants is statistically insignificant.

Table 4: Main Results

	Cox Proportional Hazard Regression				
	(1)	(2)	(3)	(4)	(5)
Product Innovation * Multi-Product Plants	-0.216***	-0.212***	-0.219***	-0.209***	-0.205***
	(0.079)	(0.079)	(0.079)	(0.080)	(0.080)
Product Innovation * Single-Product Plants	0.296**	0.303**	0.319***	0.235*	0.234*
	(0.121)	(0.120)	(0.121)	(0.130)	(0.130)
Multi-Product Plants	-0.112**	-0.139***	-0.096*	-0.075	-0.077
	(0.049)	(0.049)	(0.050)	(0.051)	(0.051)
Multi-Plant Firms		-0.952***	-0.809***	-0.855***	-2.551***
		(0.128)	(0.133)	(0.154)	(0.700)
Multi-Plant Firms * Age					0.677***
					(0.257)
Size			-0.216***	-0.165***	-0.165***
			(0.028)	(0.030)	(0.030)
Capital Intensity			-0.042**	-0.001	-0.122***
			(0.019)	(0.022)	(0.044)
Capital Intensity * Age					0.060***
					(0.020)
Labor Productivity				-0.214***	-0.019
				(0.036)	(0.078)
Labor Productivity * Age					-0.092***
					(0.034)
P-Value for Difference in Product Innovation Coefficients	0.00	0.00	0.00	0.00	0.00
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
4-Digit Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	21381	21381	21283	20497	20497

Notes: Robust standard errors clustered at the plant level in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% confidence levels, respectively. The table shows coefficients from the Cox proportional hazard regression model. The p-values shown at the bottom of all columns tests the null hypothesis that the difference in coefficients on product innovation for multi-product plants and on product innovation for single-product plants is statistically insignificant.

Table 5: Robustness Results

	Cox Proportional Hazard Regression							OLS - Linear Probability Model		Weibull		Complementary Log-Log	
	Single Plants Only	Excluding Plants with Less than 15 Employees	Innovation at 6-digit Level	Additional Industry Controls	Additional Plant Controls	Allow unique baseline hazard by 4-digit	Allow unique baseline hazard for each year	Simple	Plant Fixed-Effects IV Regression	Simple	Frailty - Assuming Gamma Distribution	Simple	Frailty - Assuming Normal Distribution
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Product Innovation * Multi-Product Plants	-0.188**	-0.246**		-0.204**	-0.207***	-0.166**	-0.210***	-0.011*	-0.303*	-0.188**	-0.345***	-0.137*	-0.151*
	(0.080)	(0.101)		(0.080)	(0.079)	(0.079)	(0.080)	(0.006)	(0.158)	(0.079)	(0.131)	(0.083)	(0.090)
Product Innovation * Single-Product Plants	0.270**	0.215		0.235*	0.242*	0.145	0.228*	0.051***	0.938*	0.255*	0.119	0.480***	0.503***
	(0.130)	(0.163)		(0.131)	(0.130)	(0.139)	(0.132)	(0.019)	(0.556)	(0.131)	(0.204)	(0.143)	(0.160)
Product Innovation 6-digit * Multi-Product Plants			-0.225**										
			(0.089)										
Product Innovation 6-digit * Single-Product Plants			0.271*										
			(0.144)										
Multi-Product Plants	-0.089*	-0.079	-0.083*	-0.077	-0.084*	-0.084	-0.076	-0.008*		-0.098*	-0.207**	-0.102*	-0.112*
	(0.052)	(0.062)	(0.050)	(0.051)	(0.051)	(0.052)	(0.051)	(0.005)		(0.051)	(0.088)	(0.053)	(0.064)
Multi-Plant Firms		-0.702***	-0.854***	-0.853***	-0.912***	-0.811***	-0.839***	-0.044***		-0.893***	-1.368***	-0.923***	-1.158***
		(0.166)	(0.154)	(0.154)	(0.155)	(0.156)	(0.154)	(0.007)		(0.153)	(0.246)	(0.159)	(0.192)
Size	-0.167***	-0.176***	-0.166***	-0.164***	-1.123***	-0.163***	-0.169***	-0.016***		-0.206***	-0.277***	-0.207***	-0.269***
	(0.031)	(0.041)	(0.030)	(0.030)	(0.107)	(0.030)	(0.030)	(0.002)		(0.030)	(0.046)	(0.029)	(0.038)
Size Squared					0.103***								
					(0.014)								
Initial Size					0.223***								
					(0.057)								
Capital Intensity	0.006	-0.042	-0.001	-0.001	-0.021	0.010	0.001	0.001		0.0001	-0.068*	0.004	0.009
	(0.023)	(0.028)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.002)		(0.023)	(0.038)	(0.021)	(0.026)
Labor Productivity	-0.215***	-0.211***	-0.213***	-0.215***	-0.221***	-0.221***	-0.226***	-0.018***		-0.197***	-0.261***	-0.216***	-0.271***
	(0.038)	(0.044)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.003)		(0.037)	(0.051)	(0.036)	(0.044)
Exporter Status					-0.020								
					(0.078)								
Foreign Ownership Status					-0.033								
					(0.129)								
Industry Sales Growth				-0.106									
				(0.116)									
Industry Herfindahl Index				1.016									
				(0.660)									
Industry Average Innovation				-0.119									
				(0.385)									
P-Value for Difference in Product Innovation Coefficients	0.00	0.01	0.00	0.00	0.00	0.05	0.00	0.00	0.04	0.00	0.00	0.04	0.00
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes
4-Digit Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19073	12433	20497	20488	20496	20497	20497	20497	20564	20497	20497	20332	20497

Notes: Robust standard errors clustered at the firm level in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% confidence levels, respectively. The table shows in columns (1)-(7) coefficients from the Cox proportional hazard regression model, and in columns (10)-(13) coefficients from Weibull and complementary log-log parametric hazard regression models. Column (9) reports the results from an IV regression where product innovation of multi-product plants and product innovation of single-product plants are instrumented using the stock of R&D expenditure for all G-7 countries in the firm's 2-digit industry and the average investment-capital ratio of the firm's 3-digit industry, respectively interacted with the multi-product plant indicator and the single-product plant indicator. The p-values of the Sargan over-identification test (0.744) as well as of the Anderson-Canon underidentification test (0.005) corresponding to column (9) suggest that the instrumental variables used are exogenous and the model is identified. The p-values shown at the bottom of all columns tests the null hypothesis that the difference in coefficients on product innovation for multi-product plants and on product innovation for single-product plants is statistically insignificant.

Table 6: Risk and Innovation Results

	Cox Proportional Hazard Regression				
	(1)	(2)	(3)	(4)	(5)
Product Innovation Accounting for Less than 50% Revenues	-0.238***				
	(0.082)				
Product Innovation Accounting for More than 50% Revenues	0.020				
	(0.105)				
Product Innovation without Product Dropping		-0.615***			
		(0.120)			
Product Innovation with Product Dropping		0.134*			
		(0.078)			
Product Innovation in an Old 4-digit Industry			-0.207**		
			(0.092)		
Product Innovation in a New 4-digit Industry			-0.098		
			(0.091)		
Product Innovation in an Old 3-digit Industry				-0.179**	
				(0.085)	
Product Innovation in a New 3-digit Industry				-0.114	
				(0.100)	
Product Innovation * Multi-Product Plants					-0.245***
					(0.086)
Product Innovation * Multi-Product Plants * Crisis					0.244
					(0.204)
Product Innovation * Single-Product Plants					0.250*
					(0.140)
Product Innovation * Single-Product Plants * Crisis					-0.093
					(0.357)
Multi-Plant Firms	-0.839***	-0.832***	-0.835***	-0.834***	-0.855***
	(0.153)	(0.153)	(0.153)	(0.153)	(0.154)
Size	-0.169***	-0.169***	-0.169***	-0.170***	-0.165***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Capital Intensity	-0.0004	-0.0004	-0.00004	-0.0001	-0.0006
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Labor Productivity	-0.214***	-0.211***	-0.215***	-0.215***	-0.215***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Multi-Product Firms					-0.074
					(0.051)
P-Value for Difference in Product Innovation Coefficients	0.04	0.00	0.38	0.60	
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
4-Digit Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	20497	20497	20497	20497	20497

Notes: Robust standard errors clustered at the plant level in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% confidence levels, respectively. The table shows coefficients (rather than hazard ratios) from the Cox proportional hazard regression model. The p-values shown at the bottom of columns (1)-(4) test the null hypothesis that the difference in coefficients on cautious innovation and on non-cautious innovation according to various definitions is statistically insignificant.

Appendix Table 1. Variable Definitions

Plant Age	Difference between the current year (in the period 1996-2003) and the first year that the plant entered the ENIA (starting in 1979).
Plant Size	Logarithm of the total employment - measured by the number of workers - of the plant.
Plant Capital Intensity	Logarithm of the capital-employment ratio of the firm. Capital is constructed as defined in Fernandes and Paunov (2008).
Plant Labor Productivity	Logarithm of sales deflated by plant-specific price indices over total employment. Plant-
Plant Foreign Ownership Status	Dummy variable that indicates whether the plant has any positive share of foreign capital.
Plant Export Status	Dummy variable indicating whether the plant exports a positive share of its output.
Industry Sales Growth	Logarithm of the difference in 4-digit ISIC industry sales between year *t* and year *t -1* .
Industry Normalized Herfindahl Index	H*=(H-1/N)/(1-1/N) where H is the Herfindahl index computed as the sum of the squares of the market shares of all N firms in the 4-digit ISIC industry and year. H* ranges from 0 to 1 with 1 indicating more concentration.
Industry Average Innovation	Average share of firms introducing new products by 4-digit ISIC industry and year.
U.S. Patents (used as instrument)	Patent counts based on applications filed under the Patent Cooperation Treaty based on the date of application and the applicant's country of residence, the United States, deposited at the European Patent Office by 2-digit ISIC industry and year from the OECD.
Average Investment-Capital Ratio (used as instrument)	Ratio of the sum of overall investment of all Chilean plants to the overall capital stock of all Chilean plants by 4-digit ISIC industry and year.