Boon or Boondoggle? Business Incubation as Entrepreneurship Policy

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ABSTRACT

Business incubators—organizations created to help small and young firms become stable and profitable—are a mainstay of economic development programs. This study looks at whether having been incubated helps new ventures survive and grow in the long-run using a nationally representative sample of incubated firms and a matched control group of non-incubated firms. New venture performance is measured as survival, employment growth, and sales growth and outcomes are used to test predictions from organizational evolutionary theory. Results reveal that the effect of incubation on new venture performance hurts the lifespan of new ventures while it helps them grow at faster rates in terms of employment and sales.

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> The heart of a true business incubation program is the ongoing, personalized, and comprehensive services that are provided to clients. By following best practices, an incubator will customize its mission, clients targeted, services provided, and infrastructure that is required in order to integrate its program into the fabric of the community and the broader economic development goals of the region. A best practice incubator will provide the expertise, networks, tools, and a social capital environment that will dramatically enhance the success of a new entrepreneurial venture. An incubator can become the catalyst for the creation of a business cluster in a community, county, state or region by creating concentrations of interconnected companies, suppliers, service providers and associated institutions.
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> —Lou Cooperhouse, Director, Rutgers Food Innovation Center
> March 17, 2010 hearing of the House Committee on Small Business

For years, policymakers and economic development experts have lauded the scope and reach of business incubators—institutions that provide subsidized space and management support to new ventures. Having grown from 12 in 1980 to approximately 1,400 today, business incubators receive generous financing from government, investors, and universities who believe incubators will increase economic growth by nurturing good business ideas into profitable new ventures. But do they? To date, little systematic knowledge exists about the value of incubation services to a new venture's competitiveness in the external environment.

New businesses could certainly use the help. Over half of new businesses fail in five years (Cressy, 2006), while profits for the typical surviving firm hover around $39,000 per year (Shane, 2008). Yet despite this lackluster performance, for the last 30 years local governments have shifted their economic development strategy away from retaining and attracting large incumbent firms (Bartik, Boehm, & Schlottmann, 2003) to encouraging individuals to start businesses that can exploit new opportunities and grow quickly (Pages, Freedman, & Von Bargen, 2003). Business incubators are one such strategy and this study investigates whether business incubation helps new ventures survive and thrive in the external marketplace in comparison to unincubated businesses.

This is an important line of empirical inquiry because incubation itself is theoretically questionable. Indeed, the assumed benefits of business incubators contradict the logic of market competition and evolutionary theory (Aldrich, 1999). Aldrich posits that the processes of firm selection and retention occur at two levels—internally within organizations and externally in the environment. While internal selection protects organizations from the pressures of the external environment, it can also stymie their ability to adapt to a competitive external environment. Hence, while incubation might insulate a firm from competitive forces of the external environment and increase its likelihood of short-term survival, incubation could also weaken the firm's ability to compete and survive once it leaves the incubator.

Although the study of incubation dates back to the 1980s, there is scarce quantitative empirical research that evaluates the effects of incubation on new venture performance. DiGregorio and Shane (2003) and Rothaermel and Thursby (2005) are among the few to apply statistical analysis to incubation performance questions. However, both of these studies omit control groups of unincubated new ventures and thus fail to address the important question of the relative advantages or disadvantages of incubation. Given the lack of robust research that examines the effects of incubation on new ventures, this study investigates whether incubated businesses outperform unincubated firms.

The data and design of this study follow the classic quasi-experimental model with a treatment group, matched control group, and longitudinal observations. I conducted analyses at the firm level using propensity score matching to estimate the average treatment effect of incubation in a sample of approximately 35,000 incubated and unincubated businesses. I estimated the average treatment effect in three ways—as sales growth, employment growth, and survival independently—while controlling for characteristics such as industry, the race and gender of the entrepreneur, and location and time fixed effects.

In the paper that follows, I first draw on the concept of liability of newness to explain how incubators help new ventures diminish risks that lead to failure due to their lack of market experience and legitimacy. This section outlines the logic behind why incubation is believed to help new ventures. I then discuss evolutionary theory to describe the possible long-term effects of incubation on new venture performance. I follow-up with a presentation of the data collected and the estimation techniques employed. I conclude with results of the study, along with limitations and future areas of research.

Business Incubation and the Liability of Newness

A business incubator is an organization that supports the creation and growth of new businesses by providing subsidized office space, shared administrative services, access to capital and financing, networking opportunities, and assistance with legal, technology transfer, and export procedures (Allen & Weinberg, 1988; Erlewine & Gerl, 2004; Hackett & Dilts, 2004). The fact that 61.5% of new firms close within five years of founding motivates those who create business incubators and those who seek incubation services (Geroski, 1995). Local governments and policymakers support business incubation because they assume incubators can generate employment, innovation, and growth by helping new businesses avoid failure (Erlewine & Gerl, 2004). Likewise, new businesses seek incubation to access knowledge and assistance that will allow them to develop, test, and market new goods and services at a profit.

A key assumption that this study tests is whether business incubators help new firms overcome the liabilities of newness. When new firms enter a market, their survival often hinges on their ability to overcome three forms of novelty: market, production, and management (Shepherd, Douglas, & Shanley, 2000). Being new to a market, to production processes, and to management can hinder a firm's survival and growth until the firm establishes legitimacy, efficiencies, and organizational systems (Shepherd, Douglas et al., 2000) that enable it to maintain a flow of heterogeneous resources necessary for production and exchange (Nelson & Winter, 1982).

Novelty to the market describes the degree to which customers are familiar with a new venture (Shepherd, Douglas et al., 2000). When a firm enters a market, it faces a competitive disadvantage due to its lack of customer loyalty (Porter, 1980) and legitimacy as a viable provider of a valued product or service (Aldrich, 1999). Without a secured customer base and a viable product, new firms also lack the legitimacy necessary to secure financing crucial for establishing and growing operations (Aldrich, 1999). Novelty to the market is difficult to overcome when a firm enters an already established industry and when it attempts to enter a completely new industry (Aldrich, 1999).

Novelty in production reflects the extent to which entrepreneurs are experienced with the technology and manufacturing processes used to deliver a product or service (Shepherd, Douglas, & Shanley, 2000). When entrepreneurs lack experience in the production processes being employed, costs of time and money may increase, especially if these processes rely on new or unproven technologies. Additionally, entrepreneurs may struggle with improving and discovering efficiencies in production processes if they are novel, which can delay the creation of economies of scale (Porter, 1980). Finally, the pressure to overcome novelty in production can create internal conflict in new ventures that leads to failure. This is especially the case in new ventures with dangerously low levels of resources. When innovation teams incur high levels of conflict, it has been shown that the ability to succeed at innovation dramatically falls (De Dreu, 2006).

Finally, novelty to management hinders new venture survival when the entrepreneur lacks adequate managerial skills, prior working experience with a start-up firm (Fairlie & Robb, 2008), or relevant industry experience (Shepherd, Douglas et al., 2000). Because starting a new venture is risky, involves coping with uncertainties, and requires both generalist and specialized knowledge, new ventures can fail if entrepreneurs lack skills and abilities that can help them organize and manage a business. In fact, studies show that entrepreneurs who invest first in management and organizing activities generally succeed in raising the legitimacy of their business, which aids in securing resources (Delmar & Shane, 2004). Additionally, it is known that venture capitalists pay particular attention to the management experience of potential investment prospects and that they generally choose to invest in entrepreneurs with high levels of management experience (Shepherd, Douglas *et al.*, 2000). Furthermore, entrepreneurs who seek venture capital and are denied investments often attribute their lack of financing to their low quality and quantity of managerial experience (Shepherd, Douglas *et al.*, 2000).

Combined, a new firm's novelty to the market, to production, and to management impede its growth and threaten its survival (Porter, 1980). Because new entrants into a market might be undercapitalized, unknown, and inexperienced, they potentially face strong retaliation and price cutting from incumbents wishing to protect their market share and profits (Porter, 1980). Additionally, new ventures face internal challenges, such as generating production efficiencies and functional administrative processes that can cause them to fail. In order to help reduce these risks of failure, business incubators have emerged to help new ventures offset their lack of financial, technical, and management capacity. By offering free or subsidized space and management training, business incubators protect new ventures from the full forces of the external competitive environment and reduce barriers to market entry (Porter, 1980). Business incubators believe their services strengthen new ventures so that they can emerge from the incubator and compete successfully in their local economy (Erlewine & Gerl, 2004).

In sum, the services that incubators provide to new ventures essentially seek to lower their liability of newness. Specifically, businesses incubators appear to address most directly a firm's novelty in production and novelty to management. Business incubators often rely on a network of experienced business leaders and management consultants to mentor and train their tenants (Erlewine & Gerl, 2004). These experts exert strong pressure towards conformity with standard business practices and thus help new ventures establish legitimacy (Aldrich, 1999). Therefore, if incubators are truly successful in lowering firms' liability of newness by helping them address their novelty to management and production, one would expect new ventures to have increased survival rates and faster growth while in incubation.

However, incubation could also have a negative effect on firms' outcomes, especially when it comes to survival. Perhaps the experience necessary to overcome the liability of newness in production and management cannot be addressed through training once a business has formed. In such cases, survival and growth may depend more strongly on experience, the industry that the firm entered, or initial assets than on access to low rent and business training. Also, it could be that firms that seek incubation services do so because their owner is less experienced or the venture is highly risky in comparison to similar types of ventures that do not seek incubation support. In such cases, the effects of incubation may not be able to compensate for the effects of risk factors that a new venture is born with. Regardless, incubators and their supporters generally assume that incubation helps firms stay in business and grow faster even when taking into consideration the attributes of the owner and the firm.

Business Incubation and Organizational Evolutionary Theory

Unlike many organization and economic theories that ignore the forces that bring firms into being, organizational evolutionary theory seeks to describe the social, economic, and technological forces that give rise to new organizations and that change the nature of those organizations' functions and purpose over time. The perspective of this theory is longitudinal and thus makes its application to assessing the emergence, survival, and growth of new ventures relevant. Evolutionary theory describes four processes—variation, selection, retention, and struggle—to describe how populations of organizations emerge and vanish (Aldrich, 1999). In this study, I am particularly interested in testing assumptions regarding selection and retention of incubated businesses because determining whether incubation helps should entail demonstrating not only higher performance during incubation but higher performance post-incubation as well.

Variation occurs when individuals and organizations change their routines, competencies, or structural form (Aldrich, 1999). Such changes can be intentional and planned or can occur through luck or mistake. For example, when organizations invest in R&D they may create new production methods that improve on standard practices. This type of intentional variation contrasts with variations created blindly such as when organizations in moments of crisis resort to improvisation to mitigate losses. Improvisation in such a case may lead to discovery of new routines that improve on past organizational processes (Aldrich, 1999).

Not all created variations prove themselves useful to organizations, just as not all types of organizations prove themselves useful to the external environment (Hannan & Freeman, 1977).

Thus, the utility of a variation to an organization depends highly on selection processes that grant certain variations legitimacy and resources for adoption. However, the selection process is theorized to be context dependent (Levinthal & March, 1993; Nelson & Winter, 1982). Because organizations exist in open environments, their preferences are influenced by the information and expertise that they gather from their surroundings (Nelson & Winter, 1982). Furthermore, organizations learn to cope with complex and multiple potential problems by simplifying their learning and accumulating knowledge inventories to respond to unpredictable and complex problems (Levinthal & March, 1993). Thus, what organizations learn from their environment and how they process this information for future reference is cyclical and bounded within the confines of physical space. Furthermore, once organizations learn to thrive in their limited and simplified context, they are prone to failure when that context changes (Levinthal & March, 1993).

Hence, selection in the context of incubation occurs in three sequential stages. First, incubators and prospective tenants must select one another. In evolutionary theory, the relationship between an incubator and a tenant is supposed to be symbiotic—the two parties exist for distinct purposes but their interdependence is mutually beneficial (Aldrich, 1999). Incubators depend on good tenants to demonstrate success and tenants receive not only survival-enhancing services but legitimacy in the external environment.

In the second stage of selection, incubators offer advice and help tenants select routines, competencies, and structures to improve their performance and odds of survival. However, selection assistance at this second stage may weaken the tenant in the long-run because it is making choices about its routines, competencies, and structure in an environment not fully congruent with the harsher and more competitive context that exists outside the incubator. Thus, while incubation may help firms survive in the long-run especially if the positive effects of incubation overcompensate for the innate weaknesses of a new firm, incubation could also have a negative effect once the firm is prepared to exist outside of the incubator environment.

In fact, evolutionary theory asserts that when organizations are "somewhat protected from their environments" they run the risk of permanent failure by developing competency traps that inhibit their ability to adapt to an externally competitive context (Aldrich, 1999). Thus, while incubation may help tenants overcome liabilities of newness, it can also impede new ventures from achieving complete independence if incubators lead tenants to select routines, competencies, and structures that are not viable outside the incubator. For example, the early advantages given to incubated businesses might lead entrepreneurs to believe that running a successful company is easier than it really it is when no assistance is being provided. Therefore, entrepreneurs may give less attention to addressing problems that the incubator by the nature of its services reduces.

The third stage of selection occurs outside the safe confines of the incubator and the process of organizational retention described in evolutionary theory determines its outcome. According to evolutionary theory, retention occurs when organizations are allowed to capture value from their selected variations (Aldrich, 1999). When environments retain organizations and allow them to secure resources and enact transactions with other individuals and organizations, the process of evolution has effectively made a choice in preserving, duplicating, and reproducing a specific set of routines, competencies, and organizational structures. The retained organizations—those that survive and hopefully grow—are the ones which have acquired a set of routines, competencies, and organizational structure that allows them to outcompete other organizations in the struggle for scarce financial and human resources, among others (Aldrich, 1999). The implication of this third stage of selection is that retained organizations are those that figured out how to operate efficiently and legitimately within a competitive environment for scarce resources.

Thus, evolutionary theory says, tenants will fail if there is a strong misalignment between the routines, competencies, and processes they develop in the incubator and those that unincubated ventures develop on their own. This happens because incubators and their tenants face different selection and retention pressures for their own survival than stand-alone businesses do. While incubators and tenants share the same competitive environment, they survive and thrive under different norms. Incubators, especially those in universities and nonprofit settings, do not compete in a for-profit context where organizational competencies for survival differ. Incubators survive partly due to their effectiveness in leveraging legitimacy with donors and policymakers who subsidize their operations, unlike for-profit firms which need to leverage marketing and production processes to sell goods and services. Thus, business mentorship of tenants by counselors who might not be deeply involved in running a for-profit business may lead incubated firms to worst results.

Therefore, if incubation is truly a valuable service that enhances the survival and performance of new ventures, tenants post-incubation should not only survive but they should demonstrate higher overall performance than their unincubated counterparts. If incubated businesses survive at higher rates and demonstrate overall higher performance post-incubation than their unincubated peers, the finding would essentially demonstrate that incubated businesses have developed a superior set of routines, competencies, and structures that allow them to win in the competition for limited resources.

Data and measures

To test the above hypotheses, I assembled and merged three datasets: a panel of the majority of business incubators operating in the U.S. between 1990 and 2008 and two panels of firm-level data from the National Establishment Time-Series Database (NETS) provided by Walls & Associates (Walls, 2009). Since incubators exist to help new businesses, I defined the unit of analysis as new businesses founded after 1989 and less than 5 years old at the time of incubation.

Business incubator data

The panel of business incubator data consists of 944 business incubators, which have operated in 1,121 locations. I used several online archival methods to confirm all known addresses of each incubator, along with its legal status, founding year, dissolution year if applicable, and affiliation with an institution of higher education[1].

I created the most inclusive and exhaustive possible census of business incubators by collecting membership rosters of the National Business Incubation Association, 23 state associations of business incubators, and economic development resource lists from 50 state governments. Because the majority of business incubators incorporate as nonprofit organizations, I also conducted a search for incubators using the master file database of the National Center for Charitable Statistics (NCCS), a clearinghouse of data on the U.S. nonprofit sector. In addition, I cross-referenced one national roster from the University of Central Florida Business Incubation Program for the year 2007.

[1] In special circumstances, where online research methods did not succeed in confirming all variables of interest for each incubator, I resorted to a short e-mail survey to acquire missing data, which garnered a 45% response rate.

To avoid overrepresentation of successful and younger incubators an additional search for incubators having closed since incorporation and those recently formed was conducted by Walls & Associates using the NETS. Because approximately 30% of the organizations in the master list contained the term “incubator” in their name, a search was done using the term’s root “incubat.” The search identified an additional 130 business incubators, many of which had ceased operations.

Tenant firm data

Because data on failed incubated businesses is more difficult to find than data on successful incubated businesses (Hackett & Dilts, 2004), I extracted a sample of all incubated businesses from the NETS using address matching techniques. The NETS is a longitudinal dataset of over 36.5 million business establishments built from annual snapshots of Dun & Bradstreet (D&B) data (Walls, 2009). The NETS includes key geographic, descriptive, and performance data for businesses, such as every known address for a firm, the year in which a business moved into or out of a particular address, industry codes, founding year, and annual sales and employment figures (Walls, 2009).

D&B defines business establishments as a “business or industrial unit at a single physical location that produces or distributes goods or performs services” (Neumark, Zhang, & Wall, 2005). This characteristic of the NETS database was crucial to conducting an address-based query to extract a population of likely incubated businesses. By matching the known physical addresses of the business incubator population with all current and former physical addresses of the 36.5 million businesses in the NETS, a data extract of approximately 38,000 likely incubated businesses was pulled.

Culling of tenant data

To finalize the incubator tenant population, several culling steps were required. First, firms founded prior to 1990 were eliminated because NETS does not provide annual performance data before that date. Then all businesses sharing an incubator's address but incorporated as nonprofits or falling under SIC codes for government were dropped. Because this study focuses only on the incubation of new and young businesses, I also dropped all firms that were over 5 years old at the time that their associated incubator was born. Firms with an initial employment of over 100 and those determined to be large corporations were also dropped[2]. Finally, all firms that were started at an incubator's address after that incubator had ceased operations were eliminated. These culling steps reduced the initial sample of 38,000 potentially incubated businesses to approximately 19,000.

To assess the accuracy of the address matching process in identifying all former and current tenants of business incubators, a data audit was conducted. A random sample of 65 incubators and their matched tenants (1,200 firms) was pulled from the remaining dataset. I then surveyed the 65 incubators via e-mail, asking their managers to report which of the listed firms were current or former tenants. The survey generated a 49% response rate and revealed that 78% of the listed firms were current or former tenants[3].

[2] Based on the definition of incubation and the entrepreneurship literature, I limit my sample to those firms deemed to be young and small-medium enterprises at the time of incubation. Thus, a young firm implies that the firm is under the age of 5 at the time it gets incubated. In addition, a small-medium enterprise restriction is used to exclude large public corporations from the analysis. For example, many incubators co-exist in business parks and commercial centers where multinational corporations also exist. I dropped out of the sample all firms which were clearly large corporations operating on their own but happening to share the same building and/or physical address as a business incubator.

[3] It should be noted that, through further investigation, I uncovered inaccuracies in the responses from incubators. In some cases, respondents did not recall accurately former clients, especially if the incubator was larger and older and the respondent was new to the incubator's staff. In other cases, responses were misleading. In one case, a respondent reported that several listed businesses were not clients of the incubator but upon calling one of the clients directly, I discovered that the firm was still operating within the incubator. In other cases, I found out through research using the Internet Archive that several businesses that were reported to not have been tenants of an incubator were actually listed as tenants on an incubator's website in prior years. Due to the errors in reporting, I suspect the accuracy of my matching strategy is actually higher than 78%.

Unincubated control group

This study relies heavily on quasi-experimental methods for estimating the average treatment effect (Rosenbaum, 2002). These methods are designed to avoid the problem of selection bias (Rosenbaum, 2002). Because it is impossible to observe simultaneously the outcome of the same firm under incubation and without incubation, matching techniques were necessary to identify a valid control group that allows for outcome comparison between incubated businesses and unincubated firms (Caliendo & Kopeinig, 2008). A valid matching method is especially necessary when random assignment into treatment and control groups is not feasible. A key assumption made when using these methods is that matching treated and untreated units on observables results in equivalent distributions of observed covariates among both groups (Rosenbaum, 2002).

Therefore, the design and extraction of an unincubated group of firms from the NETS required two steps. Because I did not have unlimited access to the full universe of the NETS database in order to extract multiple samples under different assumptions of relevant observed covariates that could predict incubation, I needed to design a general first-stage matching process that would create a database reflecting the full universe of unincubated businesses contained within the NETS. Candidates for matching were firms that were not incorporated as nonprofits and which never resided in one of the 1,121 addresses were incubators had existed.

In the first stage, each incubated business was matched to approximately seven unincubated firms based on founding year, county, industry, and the gender of the entrepreneur. Due to the high dimensionality of some of the observed covariates (i.e. founding year, county codes, and industry) (Caliendo & Kopeinig, 2008), an exact one to one matching technique was ruled out because it would have resulted in many unmatched cases. Hence, I created 420 matching strata that represented the general founding years, county codes, industry, and entrepreneur's gender of the approximately 19,000 incubated businesses. These 420 strata reflected seven general geography codes, five ranges of founding years, six industry groups, and two gender categories. For each incubated business that fell into one of the 420 strata, seven randomly matched firms without replacement were pulled out of the NETS. This dataset represented the universe of unincubated firms within the NETS, which were similar to the incubated businesses in terms of geography, founding year, industry, and gender of the entrepreneur.

Because not all matches for each incubated business were equivalent in terms of the four matching criteria, I conducted a second matching step that further refined the matching by selecting the three unincubated firms for each incubated businesses that were most alike. In order to cull the three closest matches, I used a propensity score, defined as the probability of receiving treatment given observed covariates (Rosenbaum, 2002). The use of a propensity score to create a matched dataset helps overcome the problem of dimensionality within observed covariates that makes exact one to one matching difficult (Caliendo & Kopeinig, 2008)[4]. Also, the propensity score acts as a balancing score that adjusts the distribution of observed covariates between treated and control groups. Propensity score matching helps reduce bias in observational studies when nonrandom assignment to treatment is not possible. The validity of propensity score matching rests on the assumption that matching treated and untreated units with similar probabilities of receiving treatment allows for direct comparison of outcomes. In other words, if one can estimate a model for determining treatment using observed traits of treated and untreated cases, then one can create valid comparison groups without randomization (Rosenbaum, 2002).

[4]Note that propensity score matching was deemed to risky to conduct by Walls & Associates since they had not implemented this method before.

Thus in the second stage of matching, I calculated a propensity score for each incubated and unincubated business in my dataset that took into account 50 state dummy variables, 1,048 county dummy variables, founding year, nine industry dummy variables, and two dummy variables for gender and racial identity of the entrepreneur. Based on the calculated propensity scores, each incubated business was matched to its three nearest unincubated neighbors with continuous replacement.

In order to determine that incubated and unincubated businesses shared similar likelihoods of incubation, I compared the density and distribution of their scores using a propensity score histogram (see Figure 1). Based on the low levels of overlap for propensity scores higher than 0.5, I decided to drop those cases from the analysis.

Furthermore, I also conducted two tests to determine whether matching based on propensity scores had generated similar distributions of matching covariates for treated and untreated cases. Table 1 presents the mean values of the observed matching variables prior to matching and post-matching, a t-test for their equality, and a percentage for the standardized bias due to their differences. After matching if the t-test for equality of means is rejected and the standardized bias is over 5% for any matching variable, there is reason for concern that the propensity score matching process yielded poor results (Caliendo & Kopeinig, 2008), which is not the case with any of the matching variables employed in the study.

Descriptive Statistics

Table 2 presents descriptive statistics on incubated firms and their non-incubated peers after matching and trimming of observations. Looking first at matching variables, the typical founding year for both groups is 2000. At 0.5%, minority owned firms make up a miniscule percentage of all incubated firms, while women owned firms make up 6.1% of incubated firms. Looking at industry classifications, incubated firms overwhelmingly compete in the services sector. 59% of incubated firms fall in this sector, while the next highest group of incubated firms, 11%, competes in the finance and insurance industry. These figures reflect the general trend of entrepreneurs starting businesses in the professional and personal services sector (Shane, 2008).

In terms of age and survival trends, the average incubated firm stays in business for a total of 5 years and 42% of incubated firms close by the time they are 3.63 years old. This percentage of closure for incubated firms is better than general estimates of firm failure that predict that 50% of new firms will fail within 2.5 years (Cressy, 2006).

Graduation rates are a key benchmark for business incubators. They reflect the ability of incubators to help their tenants achieve economic stability and overcome the liability of newness so that they can compete independently in the external environment. However, based on the data collected, incubators are failing in this respect. Only 4% of the sample or 655 incubated firms, managed to exit their incubator, over an 18-year period, having spent an average of 3.84 years in the incubator. Therefore, among the 18,426 incubated firms in the study, 7,543 of them closed while in incubation, 193 of them closed after incubation, 464 of the graduates remain in operations, and the remainder, 10,226, continue operating in the incubator. On average, an incubated firm spends 4.5 years in incubation.

Based on these observations, it appears that much of the success that incubators and policymakers claim is overstated. One possible explanation for my lower number of total incubated firms is that my census still left out many former and current incubators. In addition, the NETS only gathers information on businesses that have applied for a DUNS number. Perhaps the larger tenant figure from the business incubation industry includes a population of selfemployed individuals who have not incorporated and applied for a DUNS number. Despite these potential drawbacks in the data, it still appears that incubators are not fulfilling their goal of preparing new ventures to survive and thrive outside the safety of the incubator.

Comparing sales figures between the incubated and control groups, incubated firms have higher sales. They average $693,000 in sales their first year in business in comparison to the control group which averages $437,000 in their first year in business. Overall, average annual sales growth declines in both groups over the long-run. The decline is larger for unincubated firms, which average a 3% decrease in sales annually in comparison to incubated firms, which average a 1.26% decrease in sales annually. This implies that business incubators slow down the rate of demise for their tenants in comparison to the control group.

A comparison of employment figures between both groups reveals similar trends. Incubated firms are larger, with an average of 4.43 employees versus 3.45 employees for the control group. In terms of employment growth over time, incubated firms also outperform their counterparts. Incubated firms increase employment by 3% annually in comparison to the control group, which averages 0.74% annual employment growth.

This review of the descriptive statistics point to the importance in controlling for the initial size of the firms since incubated firms tend to emerge as larger organizations. This larger size may be due to unobserved selection bias where incubators are selecting tenants with more resources initially. The differences in initial size between the two groups offers some evidence of possible lurking unobserved covariates and encourages use of estimation techniques that control for omitted variable bias and tests for the possibility of endogeneity of the treatment variable.

Performance Measures

I used three performance measures—survival, employment growth, and sales growth—which were selected for their theoretical and policy implications. Empirically, we know that new businesses are slow to grow and that firm survival is a stronger measure of firm performance when firms are young (Geroski, 1995). Yet, a strong motivation for why policymakers support entrepreneurship programs is the claim made by business incubators that they speed up the growth process, especially in regards to employment (Hackett & Dilts, 2004). On the other hand, entrepreneurs pay most attention to metrics like sales and revenue growth (Davidsson & Wiklund, 2006).

Following much of the firm growth literature which relies heavily on Gibrat's proportional growth model (Coad, 2007a; Sutton, 1997), I defined growth as the log difference in firm size, $Growth_{i,t} = log(SIZE_{i,t}) - log(SIZE_{i,t-1})$. Thus, sales growth is the log difference between annual sales at time t and sales at time t-1.[5] Similarly, employment figures were first log transformed and then differenced in order to calculate annual employment growth. Firm closure was measured by examining the last year in which a business was active in the NETS. Firm failure is a dummy variable equal to 1 if the last year of activity reported by the NETS is not 2008.

Theorized Explanatory Variables

Incubation. *Incubation* is a dummy variable that equals one for incubated firms in the years in which they happen to share the same address as an incubator.

Post-incubation. *Post-incubation* is a dummy variable that equals one for formerly incubated firms in the years after which they shared the same address as an incubator.

Standard Control Variables

[5] Annual sales figures were first adjusted to 2008 dollars based on the consumer price index before being log transformed.

I controlled for several firm level effects: firm-size, firm-age, and industry. In addition, in the survival function, I controlled for the gender identity and racial identity of the entrepreneur, which are two traits that have been shown to relate to the performance of new ventures (Fairlie & Robb, 2008). Because smaller firms tend to grow faster than larger firms, controlling for firm-size effects is important (Coad, 2007b). Therefore, *sales lag* measures firm size when the dependent variable is *employment growth* and *employment lag* measures firm size when the dependent variable is *sales growth* or *firm survival*. Switching measures of firm size in relation to the dependent variable is necessary to avoid statistical bias due to autocorrelation when a lagged dependent variable is included in the model.

The age of the firm is measured in years. Eight SIC dummy codes were used to control for industry effects: agriculture, construction, manufacturing, transportation, wholesale trade, retail trade, finance, and services. In addition, year dummies were used to control for overall economic trends. Table 2 lists descriptive statistics on all dependent and explanatory variables.

Estimation Procedures

Because I used three control matches for each incubated firm, data for the analysis of survival and growth models were weighted. Incubated firms received a proportional weight of 1 and unincubated firms were given a proportional weight of 0.333.

Survival Analysis

Survival analysis is commonly used when the time at risk for experiencing an outcome differs among subjects, while needing to control for various treatments and demographic characteristics (Wooldridge, 2002). In this study, firms differ in their time at risk because they are born in different years. I used a parametric model with a log-logistic distribution after testing several distributions for best fit. I chose an accelerated failure time (AFT) model with a log-logistic distribution because it had the largest log likelihood value and the lowest Akaike Information Criterion value (Cleves, Gould, Gutierrez, & Marchenko, 2008)[6]. I also decided to use a parametric model as opposed to a proportional hazard model because assuming a distribution allows for full use of all observations and makes it possible to account for time-varying covariates (Cleves, Gould *et al.*, 2008). Additionally, to control for unobserved heterogeneity among firms, I modified the survival function to account for frailty (Cleves, Gould *et al.*, 2008).

Frailty models generalize the survival regression model by accounting for the presence of an unobserved multiplicative effect on the hazard function (Gutierrez, 2002, p. 23). The effect of frailty is assumed to have a unit mean and finite variance that is not directly estimated from the data and its purpose is to account for heterogeneity or random effects.

Thus, the AFT unshared-frailty regression model using a log-logistic distribution is given as (Cleves, Gould *et al.*, 2008):

$$S_\theta(t_i|x_i) = [1+\{\exp(-\beta_0 - x_i\,\beta_x)\,t_i\}^{1/\gamma}]^{-\theta i}$$

In this model, the dependent variable is time until firm failure. θ_i represents an individual's frailty. When θ_i is greater than 1, that individual is considered "more frail for reasons left unexplained" by observed covariates and thus exhibit a higher risk of failure (Gutierrez, 2002). The fact that θ_i represents an unobserved multiplicative effect after accounting for observed covariates indicates that it mirrors the cumulative effect of omitted variables (Gutierrez, 2002).

The constant, $\beta_{0,}$ represents the baseline hazard which, in its exponentiated form, signals whether the risk of failure is increasing if $e^{\beta 0} < 1$ or decreasing if $e^{\beta 0} > 1$. β_x represents the vector of coefficients that are to be estimated (Cleves, Gould *et al.*, 2008)). $1/\gamma$ represents a scale

[6] Table 3 presents a comparison of a basic treatment model under different distribution assumptions.

parameter with the specified log-logistic distribution. In the above model, x_i β_x represents the following terms, which are similar as in the sales and employment growth models.

$t_i|\theta_i$ = β_0 + $\beta_1$incubation $_{i,t}$ + $\beta_2$post-incubation$_{i,t}$ + β_3 lag_size$_{it}$ + $\beta_4$firm_age$_{i,t}$ + $\beta_5$women_owned$_{i,t}$ + $\beta_6$minority_owned$_{i,t}$ + $\beta_{7\text{-}15}$industry$_{i,t}$ + $\beta_{16\text{-}65}$state dummy$_{i,t}$

Sales and Employment Growth

Panel data analysis is often used for policy evaluation because it has been shown to reduce statistical bias due to omitted variables and unobserved, time-constant factors that affect the dependent variable and are correlated with explanatory variables (Wooldridge, 2006). However, in the case of dynamic growth models where a future value of growth is partially dependent on a current value of growth, it becomes important to adapt panel methods to address issues of endogeneity, serial autocorrelation, and heteroscedasticity. Additionally, the chosen model must address the potential problem of treatment selection bias. Despite having used a propensity score matching technique to generate equivalent distributions between incubated and unincubated firms, my review of descriptive statistics signals potential bias due to incubation assignment being determined by unobserved covariates.

To address the problem of treatment selection bias, I chose to use a double difference model, which allows for the existence of unobserved heterogeneity being present in the process that leads firms to receive incubation services. As discussed when reviewing descriptive statistics, incubated firms differ in their initial size in comparison to the control group. This indicates that incubated firms likely hold more assets and differ in important unobserved characteristics, such as the entrepreneur’s experience, education, and age. A double difference model should diminish the bias of unobserved heterogeneity as long as the unobserved traits that lead some firms to incubation are time invariant (Khandker, Koolwal, & Samad, 2009)[7]. Because time invariant differences get differenced away with panel fixed effects or first differences models, their bias can be eliminated.

Additionally, model specification of firm growth models tend to include lagged dependent variables. In order to resolve problems with endogeneity, serial autocorrelation, and heteroscedasticity that are introduced by lagging a dependent variable, I chose to use the Arellano-Bond system GMM estimator in Stata (Roodman, 2006). While a fixed effects or a first-difference estimator can solve the problem of potential selection bias due to unobserved omitted variables that predetermine treatment, these methods do not address autocorrelation and endogeneity due to inclusion of lagged dependent variables (Roodman, 2006).

In cases where one lacks a proper excluded instrument for the lagged dependent variable, an estimator with appropriate internal instruments from within the data can overcome the autocorrelation problem (Roodman, 2006). By using either the levels of growth $\text{rate}_{i,t-1}$ at t-2 and beyond or Δgrowth $\text{rate}_{i,t-1}$ at t-2 and beyond in a GMM framework, it is possible to estimate the double difference equation below, since lags 2 and beyond of growth $\text{rate}_{i,t-1}$ are orthogonal to $\Delta\varepsilon_{i,t}$. To implement the Arellano-Bond system GMM estimator in Stata, I used the user written command xtabond2 for Stata (Roodman, 2006).

The estimated model is the following:

$$\Delta\text{growth rate}_{i,t} = \beta_{0i,t} + \gamma_1\Delta\text{growth rate}_{i,t-1} + \beta_2\Delta\text{incubation}_{i,t} + \beta_3\Delta\text{post-incubation}_{i,t} + \beta_4\Delta\text{lag\_size}_{i,t} + \beta_5\Delta\text{firm\_age}_{i,t} + \Delta\varepsilon_{i,t}$$

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[7] Note that I did test the treatment variable for endogeneity using the two-stage regression methods described by Wooldridge (2002) with instruments by state that indicated if a state government had enacted a business incubation policy, a small business loans program, and/or a state sponsored venture capital fund. In the first stage results, the F-test statistic for the combined significance of the policy instruments was 11.25 revealing that they sufficiently estimated treatment. Furthermore, in the second stage, the F-test statistics did not reveal the treatment variable to be endogenous. However, the differences between pre-treatment outcome variables, which cannot be used for matching, still signal concerns with potential bias selection problems after matching.

Hypotheses

Based on the previously discussed theories of liability of newness and organizational evolution, I tested two hypotheses with the above survival, sales growth, and employment growth models.

> Hypothesis 1: Incubated businesses will outperform their unincubated counterparts, indicating incubation helps overcome the liability of newness.
>
> Hypothesis 2: Incubated businesses will outperform their unincubated counterparts post-incubation, indicating incubation helps firms adapt to the external environment.

Results

Effect of incubation on the hazard of firm failure

Table 4 presents three separate estimates with exponentiated coefficients of the effect of incubation on the likelihood to fail. Survival 1 results represent the base model without controlling for *incubation* and *post-incubation* status of firms and shows that control variables behave similarly once *incubation* and *post-incubation* status are controlled jointly. Note that in a AFT regression, the estimated coefficient relates proportionate changes in survival time to a unit change in a given covariate (Jenkins, 2005). Thus, when the coefficient is less than 1 and a covariate increases by 1, the effect of the variable is to reduce survival time by 1- β_x percent. Alternatively, when the coefficient is more than 1 and a covariate increases by 1, the effect of the variable is to increase survival time by 1- β_x percent.

Focusing on Survival 2 which accounts for the effect of *incubation* and *post-incubation*, results reveal that when firms enter incubation their expected time to failure decreases by 2%. In other words, incubated firms can be expected to go out of business sooner than their unincubated counterparts. Thus, based on this measurement, evidence exists refuting hypothesis 1 and reveals that incubation does not help reduce the liability of newness.

Furthermore, based on the significance and the larger effect of the post-incubation variable, the data show that once incubated firms graduate out of an incubator that their expected time to failure decreases further. Incubated firms that leave an incubator fail 10% sooner than their non-incubated counterparts. This finding implies that incubation does not help firms develop a stronger set of routines, competencies, and organizational structures to compete in the external environment. Instead, the protective environment of an incubator appears to inhibit firms from developing the appropriate attributes to succeed in the external environment.[8]

Examining the other control variables, there is nothing surprising about the effects of *employment lag,* a measure of firm size, and *firm age.* Many empirical studies tend to find that the risk of firm failure decreases as firms grow in size and age (Geroski, 1995). The effect of *minority owned* also follows similar trends in the literature (Fairlie & Robb, 2008). A notable effect is that of *women owned*. While past research tends to show that new women owned firms fail sooner than new men owned firms, these results show that women owned incubated firms are less likely to fail than their male owned counterparts.

Effect of incubation on employment growth

Table 5 presents the estimates of the effect of incubation on employment growth. A global F-test of estimated parameters for each model indicated that at least one of the estimated parameters was linearly associated with employment growth. Furthermore, the p-value for the

[8] The Logit results are included in Table 4 as an alternative estimation technique in order to confirm if the survival function results were reasonable. The fact that the coeffiencients for *incubation* and *post-incubation* are greater than 1 mirrors the same interpretation as the results seen in the survival models. Furthermore, this logit estimation technique allowed for direct control of firm-level random effects which diminishes the bias due to unobserved heterogenous effects.

AR(2) test statistic indicates that the instruments used in the Arellano-Bond system GMM estimator resolved the problem of autocorrelation, while the p-value for the Hansen statistic indicates that the model is properly identified. In both growth models, an increase of x units in a covariate leads to a proportional increase in percentage points on growth of $x^* \beta_x$.

In contrast to the survival models, the employment growth model 2 reveals that when firms enter an incubator their overall employment growth increases by 3.5 percentage points. This finding gives support to hypothesis 1 and indicates that incubation helps firms overcome the liability of newness by securing resources that enable them to grow at a faster rate than had they not been incubated.

In addition, the size and statistical significance of the post-incubation variable reveals that once a firm exits an incubator it is poised to grow further. Upon exiting an incubator, firms in this study increased their employment growth rate by 6.7 percentage points. Thus, this finding gives evidence to hypothesis 2 and shows that if we measure performance in terms of employment growth then incubation does enable firms to develop stronger capacities to compete and grow in the external environment.

Employment growth lag, *Sales lag*, and *Firm age* behave as other empirical studies have shown them to perform (Coad, 2007b; Geroski, 1995). *Employment growth lag* is not significant but its negative sign indicates that large growth in the previous year reduces growth in the following year. *Sales lag*, which measures size of the firm, indicates that the larger the firm the lower its future growth change which Gilbrat's proportional growth theory helps explain (Coad, 2007b; Geroski, 1995)[9]. *Firm-age* is not significant, positive but of small size.

[9] Gilbrat's proportional growth models assume that future size of firms is independent of current size . Thus, when the coefficient for firm size (i.e. *sales lag*) in the employment growth model is significant and not close to one, it implies that firm growth does depend on size. In cases where the coefficient is less than 1 it signals that

Effect of incubation on sales growth

Table 6 presents the estimates of the effect of *incubation* on *sales growth*. A global F-test of all estimated parameters for each model indicated that at least one of the estimated parameters was linearly associated with *sales growth*. Also, the AR(2) test statistic and the Hansen J statistic indicate that the Arellano-Bond system GMM estimator resolved the problem of autocorrelation and the model is properly identified.

Similar to the employment growth results, the sales growth models reveal that when firms enter an incubator their overall sales growth rate increases by 2.15 percentage points. This finding gives support to hypothesis 1 and indicates that incubation helps firms overcome the liability of newness by securing revenues that enable them to grow at a faster rate than had they not been incubated.

In addition, the size and statistical significance of the post-incubation variable reveals that once a firm exits an incubator that it is poised to grow further. Upon exiting an incubator, firms in this study increased their sales growth rate by almost 5.1 percentage points. Thus, this finding gives evidence to hypothesis 2 and shows that if we measure performance in terms of sales incubation does enable firms to compete for and extract more financial resources from a competitive market.

The behavior of *Sales growth lag*, *Employment lag,* and *Firm age* reflect similar trends in the literature (Coad, 2007b; Geroski, 1995). *Sales growth lag* is significant and its negative sign indicates that large growth in the previous year reduces growth in the following year. *Employment lag*, a measure of firm size, is significant and indicates that the larger the firm the

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smaller firms tend to grow faster than larger counterparts which makes sense given how much more growth a larger firm needs to secure to have the equivalent growth rate of a smaller firm.

lower its future growth change (Geroski, 1995). *Firm age* is not significant, negative but of small size.

Assessment of Results

In general, the findings from the three models measuring the outcomes of incubated firms signal that incubation helps new ventures grow faster in terms of employment and sales. However, what is the overall macro-economic effect of incubation on sales and employment growth given that incubated firms are expected to stay in business for a shorter lifespan?

Table 7 presents predicted trends in survival, annual employment, and annual sales for four distinct groups: the control group, all incubated firms, incubated non-graduate firms, and incubated graduate firms. I assume that firms in each group start with an average of 4 employees and $250,000 in sales. I base survival probabilities for each group on the annual average predicted survival probability using Model 2 in Table 4. To estimate annual employment, I first predicted annual employment growth for the study's sample using Model 2 in Table 5. I then calculated the average employment growth rate for each distinct group. Thus, average annual employment growth among the group of graduate firms for example, takes into account both the period when those firms were in incubation and the period post-incubation. Finally, I compounded total employment based on the group's estimated average employment growth rate and the corresponding probability of survival. Total sales was calculated similarly.

Comparing, the average incubation effect with the control group's results, it is evident that after 10 years incubation dampens total employment and total sales losses but not firm closures. The surviving incubated businesses have lost 167 jobs in comparison with the control group’s loss of 186 jobs. In other words, incubation helps incubated businesses save 19 jobs that would otherwise be lost due to the lower rates of employment growth for unincubated firms.

The predictions show that the effect of incubation on overall sales follow a similar trend. The incubated group's loss in sales is $1.2 million less than the loss in sales for the control group. After 10 years, annual sales among incubated businesses decline by $14.6 million in comparison with unincubated firms whose sales decline by $15.8 million. Based on employment and sales performance, incubation generally has a positive economic effect but it does not contribute to net economic gains since overall there are net losses in employment and sales for the incubated group.

Table 7 also reveals that over 10 years the population of incubated firms decreases more in absolute terms compared to the control group. The loss is even higher for the group of firms that graduate from the business incubator. While the employment and sales growth models predicted that incubated firms that graduate from an incubator gain additional percentage points in growth, the survival model predicted that this group would die off sooner than had it remained in incubation. Looking at the average incubation effect for graduates, it is evident that the larger predicted sales and employment growth rates for graduates are not enough to compensate for their increased failure rates due to graduation. The losses in total sales for graduates is larger than the losses in total sales for the non-graduates. More striking are the losses in total employment for the group of graduates. Their loss in employment is even larger than the control group’s signaling that incubated firms that graduate from an incubator are worse off than had they never been incubated.

This analysis of predicted trends in survival, employment, and sales reveals that incubation stems a firm’s economic loss in terms of employment and sales but that it does not contribute positively to economic growth. Firms in incubation are better off than had they not been incubated but they are still more likely to fail and not grow. What could explain these results?

One explanation may lie in the signaling and guidance that incubated firms receive. Once a firm gets incubated, an incubator's close monitoring of the performance and changing competencies of its clients may generate information that leads incubated firms which are least likely to survive in the long-run to dissolve sooner. Therefore, the accelerated failure rates for incubated firms and the effect of this failure on net gains in employment and sales may be due to an incubator's ability to weed out failing businesses in the economy much sooner than the market would. Given that incubation subsidizes operations and management training, the economist Baumol (1993) would label this effect as productive entrepreneurship since incubation leads to savings of resources that would otherwise go to production that is not efficient and rent seeking.

Alternatively, these results may indicate that business incubators are poor judges of future business performance. While surviving incubated firms do grow and growth can be explained by the cost savings of incubation, incubators fail to identify and incubate firms most likely to survive. Among the incubated, incubators are selecting more often firms likely to fail than firms more likely to survive.

A final explanation for these results centers on the predictions of organizational evolutionary theory. Because incubated businesses learn to operate in an environment that is buffered from the full forces of the external environment, they do not learn how to thrive in the more competitive external economy. While incubation helps firms grow, this growth may lead firms to assume wrongly that they are competitive since their growth is tied to subsidies of costs and management training. Thus, incubated businesses may develop incongruous competitive behaviors that rely on the help of incubation while ignoring that the market may not accept or tolerate such type of competition in the long-run.

Understanding what drives these nuanced relationships between incubation, economic growth, and firm failure requires further study. Future research should seek to study closely the financial statements of a matched sample of incubated and unincubated firms to determine how changes in costs and employment are correlated with changes in sales and profit. Acquiring such data would require implementation of rigorous survey methods or use of proprietary government databases such as the Integrated Longitudinal Business Database: Data Overview of the Census Bureau's Center for Economic Studies. This kind of research may help determine whether incubated businesses develop competitive behaviors that are unsustainable or if incubators are ignoring important indicators of future success when selecting tenants.

Alternatively, qualitative research on incubated businesses can explore whether incubation actually leads to productive entrepreneurship by accelerating the closure of unproductive businesses. Interviewing failed incubated businesses can help assess the quality of incubation services and identify mistakes that firms make while in incubation that lead to their demise. Additionally, interviewing incubated businesses regardless of failure could help probe whether selection bias exists in this study and generate ideas for how to better control for such a possible threat to validity.

Furthermore, qualitative research could help probe other predictions of evolutionary theory. Incubators often claim that they offer more than just space and that their services are more valuable because they provide important training and expertise in management and business development. Yet, these results indicate that incubated businesses make strategic mistakes in how they manage resources while in incubation and post-incubation. Perhaps because incubation subsidizes space and lowers the costs of administration through shared administrative services, incubated firms develop inefficiencies in how they manage their staffs to perform all the necessary functions that the business will need to perform once they exit the incubator. A study on how incubated firms respond to the type of counseling and training that incubators deliver may reveal potential problems in how incubated firms view incubation services and how incubators view their tenants.

Conclusion

For years, scholars have sought to know whether incubation has a discernable positive effect in the performance of their clients, while business incubators and policymakers have generally made claims that incubation is an effective service that helps firms survive and grow. This study used some of the best publicly available data, manipulated it using sound assumptions, and estimated the impact of incubation with robust estimation techniques. The findings reveal that the effects of incubation are potentially deleterious to the long-term survival and performance of new ventures. Incubated firms outperform their peers in terms of employment and sales growth but fail sooner. These are important findings for policymakers who support incubation as a strategy to increase employment locally and for entrepreneurs who risk their livelihoods in order to earn a decent living.

However, claims that incubators are highly successful and serve a significant number of businesses are overstated. The comprehensive process used in this study to identify the largest possible sample of incubated firms uncovered a fraction of the number of incubated ventures that supporters of incubation claim exist. While improvements are likely possible to the methods used in this study, this study roundly refutes the poorly documented and unpublished studies that cite much larger numbers of incubated firms and much higher levels of performance.

The methods and findings of this study showcase that more research is necessary to fully understand the effectiveness of incubation programs. Until then, these findings are instructive in helping and motivating business incubators to improve their past performance.

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TABLE 1
Bias Correction Results (Unmatched vs. Matched)

Variable	Sample	Mean Incubated	Mean Control	%bias	% Reduction Bias	t-test t	t-test p>|t|
Founding Year	Unmatched	1999	1998.5	10.7		25.55	0.000
	Matched	1999	1998.8	4.1	*61.8*	8.93	0.000
Minority Owned	Unmatched	.00608	.00632	-0.3		-0.72	0.474
	Matched	.00608	.00572	0.5	*-54.8*	1.03	0.302
Women Owned	Unmatched	.08638	.09784	-4.0		-9.44	0.000
	Matched	.08638	.09309	-2.3	*41.5*	-5.10	0.000
Agriculture & Forestry	Unmatched	.00575	.00909	-3.9		-9.12	0.000
	Matched	.00575	.00765	-2.2	*42.9*	-5.08	0.000
Construction	Unmatched	.0353	.03853	-1.7		-4.08	0.000
	Matched	.0353	.03531	-0.0	*99.7*	-0.01	0.992
Manufacturing	Unmatched	.08319	.08439	-0.4		-1.04	0.300
	Matched	.08319	.07983	1.2	*180.5*	2.67	0.008
Transportation	Unmatched	.04682	.05136	-2.1		-5.00	0.000
	Matched	.04682	.05209	-2.4	*-16.2*	-5.27	0.000
Wholesale Trade	Unmatched	.06588	.0596	2.6		6.24	0.000
	Matched	.06588	.0628	1.3	*50.9*	2.73	0.006
Retail Trade	Unmatched	.09889	.11181	-4.2		-10.03	0.000
	Matched	.09889	.10091	-0.7	*84.4*	-1.46	0.143
Finance & Insurance	Unmatched	.13369	.13571	-0.6		-1.42	0.157
	Matched	.13369	.12992	1.1	*-86.5*	2.42	0.016
Services	Unmatched	.59038	.57437	3.2		7.77	0.000
	Matched	.59038	.59376	-0.7	*78.9*	-1.50	0.135

TABLE 2

Descriptive Statistics For Incubated Firms and Control Group After Matching

		N	Average or %	Std. Dev.	Min	Max
	Incubated Firms					
*	Founding Year (ave)	18426	2000	4.19	1990	2006
	Firm Failure (%)	18426	42%	0.49	0	1
	Age (ave)	18426	5.03	3.50	1	18
	Age of Surviving Firms (ave)	10761	6.03	3.72	2	18
	Age of Failed Firms (ave)	7665	3.63	2.59	1	17
	Years Spent in Incubator (ave)	18426	4.55	3.16	0	18
	Graduates	655	4%	0.19	0	1
	Failed Graduates	193	29%		0	1
	Years Spent in Incubator (ave)	657	3.84	2.73	0	17
	Years Spent in Incubator of Surviving Graduates (ave)	464	4.10	2.89	0	17
	Years Spent in Incubator of Failed Graduates (ave)	193	3.23	2.19	0	12
	Age at Graduation (ave)	657	4.51	3.12	0	17
	Initial Sales (ave)	18397	$ 692,783	$ 7,093,375	$ 307	$805,000,000
	Latest Sales (ave)	18397	$ 695,305	$ 4,054,165	$ 500	$304,000,000
	Annual Sales Growth (ave)	74166	-1.26%	0.38	-14%	14%
	Initial Employment (ave)	18426	4.43	7.95	1	100
	Latests Employment (ave)	18426	5.81	22.93	1	2500
	Annual Employment Growth (ave)	74271	3%	0.30	-6%	5%
*	Minority Owned (%)	18426	0.5%	0.07	0	1
*	Women Owned (%)	18426	6.1%	0.24	0	1
*	Agriculture & Forestry	18426	1%	0.08	0	1
*	Mining	18426	0.08%	0.03	0	1
*	Construction	18426	3%	0.18	0	1
*	Manufacturing	18426	7%	0.26	0	1
*	Transportation	18426	4%	0.20	0	1
*	Wholesale Trade	18426	6%	0.24	0	1
*	Retail Trade	18426	8%	0.27	0	1
*	Finance & Insurance	18426	11%	0.31	0	1
*	Services	18426	59%	0.49	0	1
	*Matched Control Group ***					
		N	Average or %	Std. Dev.	Min	Max
*	Founding Year (ave)	28346	2000	4.39	1990	2006
	Firm Failure (%)	28346	42%	0.50	0	1
	Age (ave)	28346	5.00	3.75	1	18
	Age of Surviving Firms (ave)	16123	6.09	3.95	2	18
	Age of Failed Firms (ave)	12223	3.52	2.51	1	17
	Initial Sales (ave)	28290	$ 436,510	$ 2,412,547	$ 1,068	$223,000,000
	Latest Sales (ave)	28290	$ 436,660	$ 2,746,064	$ 1,000	$214,000,000
	Annual Sales Growth (ave)	116121	-3%	0.29	-5%	6%
	Initial Employment (ave)	28346	3.45	6.79	1	100
	Latests Employment (ave)	28346	4.02	13.30	1	1049
	Annual Employment Growth (ave)	116231	0.74%	0.25	-4%	6%
*	Minority Owned (%)	28346	0.4%	0.07	0	1
*	Women Owned (%)	28346	6.5%	0.25	0	1
*	Agriculture & Forestry	28346	1%	0.09	0	1
*	Mining	28346	0.08%	0.03	0	1
*	Construction	28346	4%	0.19	0	1
*	Manufacturing	28346	8%	0.27	0	1
*	Transportation	28346	4%	0.20	0	1
*	Wholesale Trade	28346	6%	0.23	0	1
*	Retail Trade	28346	9%	0.29	0	1
*	Finance & Insurance	28346	11%	0.31	0	1
*	Services	28346	57%	0.49	0	1

** Indicates matching variable*

*** Weighted statistics*

TABLE 3
Fitting Data to the Best Distribution

	Exponentiated Coefficients				
	Weibull	Exponential	Gompertz	Lognormal	Loglogistic
Incubation	0.9830**	0.9191**	1.1011***	0.9758**	0.9812**
	(0.0083)	(0.0319)	(0.0386)	(0.0097)	(0.0083)
Post-Incubation	0.9165***	0.8184**	0.9536	0.8766***	0.9070***
	(0.0204)	(0.0701)	(0.0845)	(0.0353)	(0.0232)
Employment lag	1.0023***	0.9998	1.0000	1.0024***	1.0025***
	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0005)
Firm age log			0.4847***		
			(0.0154)		
Firm age	1.2900***	1.0762***		1.2633***	1.2854***
	(0.0104)	(0.0042)		(0.0079)	(0.0103)
Minority owned	0.9628***	0.8255***	1.2330***	0.9744	0.9654**
	(0.0121)	(0.0495)	(0.0800)	(0.0243)	(0.0138)
Women owned	1.1217***	1.6656***	0.5717***	1.1708***	1.1282***
	(0.0106)	(0.0599)	(0.0235)	(0.0143)	(0.0117)
Constant	2.0020***	9.9107***	0.0977***	2.3931***	1.9802***
	(0.0827)	(0.4751)	(0.0056)	(0.0746)	(0.0774)
ln_p	4.4564***				
	(0.2104)				
gamma			1.1562***		
			(0.0102)		
sigma				0.5058***	
				(0.0145)	
gamma					0.2207***
					(0.0099)
Number_obs.	237274	237274	237274	237274	237274
Number_firms	36859.667	36859.667	36859.667	36859.667	36859.667
Log-likelihood	-3.06e+04	-3.70e+04	-3.23e+04	-2.71e+04	-2.64e+04
AIC	61362.804	74028.168	64715.036	54218.815	52912.384

NOTES: Robust standard errors in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

TABLE 4
Exponentiated Coefficients of Effect of Incubation on Firm Surival

	Survival 1(a)	Survival 2(a)(b)	Logit
Incubation		0.9812***	1.0616***
		(0.0045)	(0.0164)
Post-Incubation		0.9070***	1.2198**
		(0.0193)	(0.1052)
Employment lag	1.0024***	1.0025***	0.9997
	(0.0006)	(0.0006)	(0.0006)
Firm age	1.2850***	1.2854***	0.9223***
	(0.0032)	(0.0032)	(0.0025)
Women owned	1.1288***	1.1282***	0.5734***
	(0.0104)	(0.0104)	(0.0186)
Minority owned	0.9648*	0.9654*	1.2251**
	(0.0187)	(0.0186)	(0.1099)
Constant	1.9668***	1.9802***	0.1437***
	(0.0997)	(0.0989)	(0.0164)
Gamma	0.2208***	0.2207***	
	(0.0040)	(0.0040)	
Rho			.0000303
Frailty (theta)		0.000	
Number_obs.	237274	237274	237274
Number_firms	36859.667	36859.667	46772.000
Log-likelihood	-3.10e+04	-3.10e+04	-6.74e+04
AIC	62133.605	62098.600	1.35e+05

NOTES: (a)Weighted results (b)Robust standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

TABLE 5
Employment Growth in Incubation & Post-Incubation

	Model 1	Model 2
Incubation		0.0355***
		(0.0023)
Post-incubation		0.0665***
		(0.0122)
Employment growth lag	-0.0077	-0.0073
	(0.0071)	(0.0071)
Sales lag	-0.0470***	-0.0498***
	(0.0017)	(0.0018)
Firm age	0.0002	0.0004
	(0.0003)	(0.0003)
Constant	0.6321***	0.6553***
	(0.0240)	(0.0243)
Number_obs.	147483	147483
Number_firms	35282	35282
Instruments	41	43
Model degrees of freedom	25	27
Wald chi-squared	995.3589	1068.9515
Wald chi-squared p-value	<0.0001	<0.0001
AR(1) test statistic	-27.5777	-27.5802
AR(1) p-value	<0.0001	<0.0001
AR(2) Test Statistic	-0.5786	-0.5104
AR(2) p-value	0.5629	0.6098
Hansen J statistic	20.6210	20.6767
Hansen J p-value	0.1117	0.1102

NOTES: Robust standard errors in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

TABLE 6
Sales Growth in Incubation & Post-Incubation

	Model 1	Model 2
Incubation		0.0215***
		(0.0025)
Post-incubation		0.0513***
		(0.0147)
Sales growth lag	-0.0527***	-0.0526***
	(0.0181)	(0.0181)
Employment lag	-0.0017***	-0.0017***
	(0.0004)	(0.0004)
Firm age	-0.0002	-0.0002
	(0.0004)	(0.0004)
Constant	-0.0131*	-0.0239***
	(0.0074)	(0.0075)
Number_obs.	147478	147478
Number_firms	35280	35280
Instruments	41	43
Model degrees of freedom	24	26
Wald chi-squared	1443.9119	1523.4264
Wald chi-squared p-value	<0.0000	<0.0000
AR(1) test statistic	-15.5638	-15.5634
AR(1) p-value	<0.0000	<0.0000
AR(2) Test Statistic	-0.9801	-0.9634
AR(2) p-value	0.3271	0.3353
Hansen J statistic	17.5076	17.4320
Hansen J p-value	0.2894	0.2937

NOTES: Robust standard errors in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

Table 7

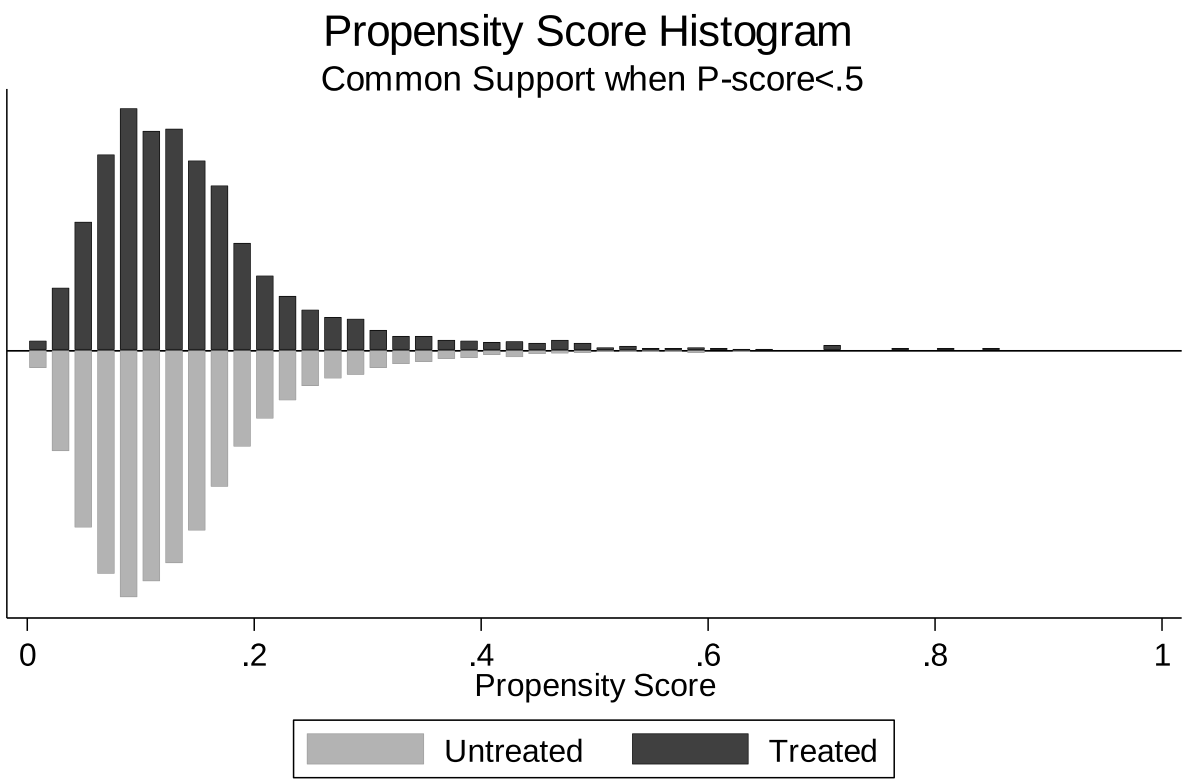
Predicted Effect of Incubation over 10 years

	Control Group				**Average Incubation Effect**			
Year	*Survival Probability*	*Total Surviving Firms*	*Total Employment*	*Total Sales*	*Survival Probability*	*Total Surviving Firms*	*Total Employment*	*Total Sales*
1		100	400	$ 25,000,000		100	400	$ 25,000,000
2	0.98	98	398	$ 23,880,324	0.98	98	403	$ 24,257,128
3	0.91	89	365	$ 21,031,013	0.90	89	373	$ 21,634,028
4	0.85	76	315	$ 17,401,774	0.85	75	324	$ 18,090,348
5	0.86	65	272	$ 14,436,921	0.85	64	282	$ 15,176,632
6	0.89	58	244	$ 12,398,263	0.88	57	254	$ 13,195,749
7	0.92	53	227	$ 11,079,020	0.92	52	239	$ 11,948,506
8	0.95	51	218	$ 10,225,757	0.95	49	232	$ 11,188,030
9	0.97	49	214	$ 9,649,515	0.97	48	231	$ 10,718,493
10	0.99	49	214	$ 9,227,084	0.99	47	233	$ 10,412,221
	Net Change	*-51*	*-186*	$(15,772,916)	**Net Change**	*-53*	*-167*	$(14,587,779)
	Ave. Annual Employment Growth = 1.1% & Ave. Annual Sales Growth = -3%				Ave. Annual Employment Growth = 2.34% & Ave. Annual Sales Growth = -1.39%			

	Average Incubation Effect for Non-Graduates				**Average Incubation Effect for Graduates**			
Year	*Survival Probability*	*Total Surviving Firms*	*Total Employment*	*Total Sales*	*Survival Probability*	*Total Surviving Firms*	*Total Employment*	*Total Sales*
1		100	400	$ 25,000,000		100	400	$ 25,000,000
2	0.98	98	403	$ 24,243,985	0.98	98	404	$ 24,405,995
3	0.90	89	373	$ 21,614,464	0.87	85	364	$ 21,274,109
4	0.85	76	323	$ 18,073,283	0.80	68	302	$ 17,080,457
5	0.85	64	282	$ 15,165,960	0.81	55	253	$ 13,857,060
6	0.88	57	254	$ 13,189,072	0.85	47	223	$ 11,820,622
7	0.92	52	239	$ 11,944,145	0.90	42	207	$ 10,628,001
8	0.95	50	232	$ 11,185,046	0.94	39	201	$ 9,951,487
9	0.97	48	231	$ 10,715,050	0.96	38	200	$ 9,591,361
10	0.99	47	233	$ 10,406,639	0.98	37	203	$ 9,412,711
	Net Change	*-53*	*-167*	$(14,593,361)	**Net Change**	-63	*-197*	$(15,587,289)
	Ave. Annual Employment Growth = 2.30% & Ave. Annual Sales Growth = -1.44%				Ave. Annual Employment Growth = 3.5% & Ave. Annual Sales Growth = .12%			

TABLE 8
Summary of Hypotheses

	Survival	Employment Growth	Sales Growth
Hypothesis 1: Incubated new businesses will perform at higher levels than equivalent unincubated new businesses.	Not supported	Supported	Supported
Hypothesis 2: If incubated firms outperform their counterparts post-incubation, then evidence exists that incubation enables new ventures to develop a stronger set of routines, competencies, and organizational structure to compete in the external environment.	Not supported	Supported	Supported



Propensity Score Histogram
Common Support when P-score<.5
0
.2
.4
.6
.8
1
Propensity Score
Untreated
Treated

Figure 1