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Effects of Aging Resources on Firm and Industry Dynamics

Scott Rockart
UNC Chapel Hill
Strategy and Entrepreneurship
scott_rockart@kenan-flagler.unc.edu

Kevin Miceli
Kenan-Flagler PhD Program
Strategy and Entrepreneurship
kevin_miceli@kenan-flagler.unc.edu

Abstract

Mainstream strategy scholars have long recognized the importance of stocks (?resources?) in explaining firm growth and performance. Under the label of the Resource Based View (RBV) of strategy, strategy researchers have been consumed with several questions about stock accumulation. Surprisingly, the literature has done little to evaluate how the value (not just the amount) of these accumulated stocks rise or fall endogenously over time. In this paper, we use a simple model to illustrate how the rise or fall in value of resources as they age affects patterns of firm performance and growth rates across industries over time. Using data on firms in 175 different industries from 2003 to 2013, we find evidence supporting our argument that the relationship between firm age and firm growth rates varies across industries as a result of differences in the nature of resource aging across industries.

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Introduction

Mainstream strategy scholars have long recognized the importance of stocks ("resources") in explaining firm growth and performance. Under the label of the Resource Based View (RBV) of strategy, strategy researchers have been consumed with several questions about stock accumulation: when are firms able to acquire stocks at a cost less than their value (Barney, 1986); how does stock accumulation influence firm expansion (Penrose, 1959); why are some firms able to accumulate stocks more effectively or rapidly than others (Argote & Epple, 1990; Dierickx & Cool, 1989); and how do stocks inhibit change in the face of exogenous environmental change (Leonard-Barton, 1992; Levitt, 1975; Rosenbloom & Christensen, 1994; Tushman & Romanelli, 1985; Tushman & Anderson, 1986)? Surprisingly, the literature has done little to evaluate how the *value* (not just the amount) of these accumulated stocks rise or fall endogenously over time. In this paper, we use a simple model of resource aging to develop hypotheses about the implications of resource aging for firm and industry dynamics. We then test these hypotheses using data on firm growth rates and resource aging in 175 industries over the period from 2003 to 2013. Consistent with the theoretical arguments, we find that firms grow more slowly initially, but grow at a higher rate later, in industries where resources grow more valuable over time. We conclude that the resource aging processes may help us to understand conflicting findings about growth rates of firms of different sizes and ages (Caves, 1998; Simon, 1964).

The basic foundation behind the RBV is that companies rely on resources (e.g., knowledge, people, property, and equipment) to compete. Given the assumed value of resources, most of the RBV has focused on how firms acquire large *amounts* of valuable resources quickly and cheaply (Dierickx & Cool, 1989; Leonard-Barton, 1992; Tushman & Romanelli, 1985). While RBV research has recognized that changes in resource *amounts* are often endogenous (Dierickx & Cool, 1989), it has largely assumed that changes in resource *value* (the profit generated by a given amount of a resource) are driven by exogenous changes such as the introduction of competing technologies or changing consumer needs (Leonard-Barton, 1992; Levitt, 1975; Rosenbloom & Christensen, 1994).

This highly aggregated view of resources, as stocks whose amounts change endogenously but whose value to the firm rises or falls only due to exogenous changes, overlooks basic endogenous stock dynamics well known to those who observe real firms. Notably, many resources pass through an aging (or development) process in which their total amount may remain the same but their value to the firm rises or falls over time even without changes in external conditions. In some cases, the value of a resource to the firm rises as it ages (e.g., inventories of wine and spirits; employees learning on the job; and products and production technologies subject to continuous improvement) while in other cases the value of a resource declines as it ages (e.g., workers whose healthcare costs, seniority-based pay, and pension payments rise faster than their productivity; and equipment that degrades or whose maintenance costs rise).

In this paper, we argue that resource aging and the distinction between resources that gain value with age and resources that lose value with age is a key and systematic influence on firm growth rates and as a result on broader patterns of industry dynamics. Using a simple dynamic model, we show that when resources gain value as they age, firms can be expected to grow more slowly initially but their growth rates will be higher later. Using data on firm growth rates we find evidence consistent with our hypotheses, in brief, we find that firms in industries where resources rise in value over time grow more slowly initially but later grow at a higher rate.

Basic Model and Implications

We use a very simple model to illustrate how resource aging generates these patterns of firm dynamics (Figure 1). For brevity, the model captures the aging process of resource stocks with just two variables, one variable represents a firm's stock of newer resources (R_n) and the other represents the firm's stock of older resources (R_o).[1] The basic dynamics of resource aging occur in the model as a firm's resources are first acquired, age, and then are eventually discarded. Specifically, the stock of newer resources (R_n) increases with an inflow of resource acquisitions (a) and decreases with an outflow representing the new resources aging or 'maturing' (m) (equation 1). Similarly, the stock of older resources (R_o) increases as the firm's new resources age (m) and become older resources and the stock falls as older resources reach the end of their useful life and are discarded (d), (equation 2).

$$R_n = \int_0^t (a - m)\delta t + N_0$$

Eq.1

$$R_0 = \int_0^t (m - d)\delta t + M_0$$

Eq.2

[1] Basic results are unchanged if we apply a much more detailed model of resources over a continuum of ages.

To capture our basic argument, that the age of a firm's resources influences firm performance, we model firm performance (ρ) as a weighted average of the two resource stocks (R_n, R_o). The weights (v_N, v_o) allow the model to capture situations in which the newer resources are more valuable than the older resources $(v_N > v_o)$ as well as the situations in which the older resources are more valuable than the newer resources $(v_N < v_o)$, (equation 3).

$$\rho = v_N R_n + v_o R_0$$

Eq.3

While the stock equations capture the basic physics of aging (new resources are acquired, become old, and are eventually discarded), and our performance equation simply captures our argument that the age of a firm's resources affects firm performance, we must still determine how to capture the flows of those resources in and out of the resource stocks (a, m, d). Two of these three flows of resources (m, d) are driven simply by time, the amount of time required for a new resource to become an old resource (θ) and the amount of time it takes an older resource to reach the end of its useful life (ϕ) (see equations 4a,b).

$$m = \frac{R_n}{\theta}, \quad d = \frac{R_0}{\phi}$$

Eq.4a,4b

This leaves only an equation for the resource acquisition rate (a) to complete the model. We begin with the base assumption known as Gibrat's Law, that firms grow their total resources $(R_n + R_m)$ at a constant fractional rate (γ) (Simon & Bonini, 1958). We then amend this to bring in an effect of resource age by assuming, as Demsetz (1973) argued, that higher preforming firms tend to grow more rapidly. We capture the relationship between firm performance (ρ) and grow rates using a logit formulation where (α) scales how dramatically performance influences growth rates (equation 5).

$$a = \gamma(R_n + R_m)\left(\frac{\exp(\alpha\rho)}{1+\exp(\alpha\rho)}\right)$$

Eq.5

The overall model is shown graphically in (Figure 1). The model captures the very simple aging process that gives rise to an endogenous change (either rise or fall) in the *value* of a firm's resources and as a result the firm's rate of growth.[2]

*** Insert Figure 1 about here ***

An inescapable implication of any endogenous change in resource value, whether resources become less or more valuable as they age, is that the new resource must always rise before the older resource (Figure 2). While a very straightforward idea, it still has very substantial and some subtle implications for firm and industry dynamics. Specifically, this means that later

[2] For the purpose of clarity of the figures shown later, we've assumed that it takes an average of 10 years for resources to move from new (young) to older (mature) stages, and an average of 25 years for older resources to be depleted (discarded) by the firm. While the precise values in the figures are sensitive to these assumptions, the qualitative results reported are unchanged over reasonable ranges of possible aging time assumptions.

entrants (those only a few years down the age curve shown in figures 2) will be at an advantage (have relatively high performance) when new resources are *more valuable* than older resources. For example, during the early years of many companies, employees are generally younger leading to lower pay expectations, lower healthcare costs and pension benefits, and lower turnover costs (e.g., Nucor initially boasted annual turnover of only 1%, this is possible only for a startup because in equilibrium 1% turnover means that employees remain with a company for 100 years on average). For companies with large labor costs this will generally provide a cost (performance) advantage for recent entrants (those only a few years into the curves in Figure 2 where we see more new than older resources) over earlier entrants (those well down the curves in Figure 2). In contrast, the fact that new resources must rise before older resources puts earlier entrants at an advantage whenever new resources are *less valuable* than older resources. For example, in many industries the stocks of customer relationships become much more valuable over time as high levels of trust are developed and as customers and firms have adapted their practices and processes (e.g., technological adaptations and physical locations of property and plant) to work uniquely well with the established firms. Due to the higher value of these older resources, established firms will have an advantage over later entrants.

*** Insert Figure 2 about here ***

The magnitude and length of the advantages that this basic feature of aging chains can impart will depend on a variety of factors that vary from industry to industry. One of these factors is how quickly resources mature. For example, if the resource remains new for considerably longer than it remains with the firm in a older state, both early and late entrants will have a high ratio of new to older resources. Short periods in the older resource stock may explain why older retail firms such as Starbucks continue to benefit from relatively healthy workers with low pay expectations. Most mature workers leave voluntarily (have a low depletion time) and fairly quickly to look for employment with greater skill development potential and better long-term career prospects. This allows the new stock to remain high relative to the older stock even as firms themselves age. In contrast, when resources remain mature for much longer than they are new, older firms develops a very high ratio of older to new resources. For example, early entrants in industries that rely on large investments in heavy equipment often find that they are saddled with equipment that is long lived (has a long depletion time because of the cost to remove and reconfigure) and becomes increasingly unreliable and expensive to maintain as it ages. Older firms in these industries will become increasingly disadvantaged relative to new entrants due to the slow depletion of resources that are both long-lived and decreasing in value. Similarly, for rehabilitation hospital chains in the 1990s, new hospitals were more profitable than mature hospitals because Medicare and Medicaid provided generous reimbursement for new hospitals (cost-plus contracts) to encourage expansion of access to care. Rehabilitation hospital chains further down the age curve were burdened with a higher proportion of older hospitals putting them at a disadvantage relative to firms only a short way down the age curve.[3]

Figure 3 compares the growth paths of firms (changes in the total of both new and older resources over time) when resources either fall in value over time $(v_N > v_o)$ or rise over time

[3] An extreme version of this structure is often called the Pyramid or Ponzi Scheme, where those in the new stocks (new members of the scheme) provide all the value that is consumed by those in the older stocks. Older schemes, where growth has slowed and the ratio of new to older resources has fallen, are at increasing risk of collapse.

$(v_o > v_n)$

.[4] This comparison provides the basis for our tests of the effect of resource aging. We see that firms in an industry where new resources are more valuable grow rapidly at first, then their growth slows.[5] In contrast, firms in an industry where older resources are more valuable grow slowly at first, but notably their growth rate does decline as rapidly over time. The comparison of these two patterns defines our two hypotheses:

Hypothesis 1: Firm growth rates will be lower initially in industries where resources rise in value over time

Hypothesis 2: Firm growth rates will be higher for older firms in industries where resources rise in value over time

*** Insert Figure 3 about here ***

METHODS

Setting and data sources

To test the hypotheses, we choose one key example of an aging resource – human capital. We choose human capital in part because of the obvious aging, and in part because it is a key resource in almost any industry. Since we believe that the nature of aging of human capital differs largely across industries we looked for panel data with coverage of multiple industries. We then apply this in a large panel data set based on European data using OLS, panel regressions, and selection tests.

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[4] For the simulation labeled "New Resources Higher Value," the value of a new resource is set at 0.25 and the value of a older resource is set at -0.25. For the simulation labeled ("Older Resources Higher Value") the settings are reversed.

[5] In this run the growth rate slows so much that the firm begins to decline, we focus on the slowing of growth rather than the appearance of decline because growth may slow down but still be positive.

The National Longitudinal Survey of Youth (NLSY), which is conducted by the Bureau of Labor Statistics, provides our indicator of whether human capital rises or falls in value in a given industry as people age. We use the "1979 Survey" which tracks individuals from their youth starting in 1979 forward. It is a nationally representative sample of nearly 13,000 men and women who were born in the years 1957-1964 and were ages 14-22 years when the survey began. They were interviewed annually until 1994, at which time the survey was presented biennially (Bureau of Labor Statistics, 2013).

Orbis provides our data on the size, age, and growth of firms across multiple industries. The database is owned by Bureau van Dijk (BvD) which collects public and private data on pan-European companies (Green, 2003). BvD combines the information, with a focus on the quality of private data and presents financials in a standard format that can compare firms across national borders. Data is provided for the previous ten years from the date of access, so we use data from 2003 to 2013.[6] The database allows us to see a wide range of sizes and ages of firms with the broad coverage as compared to other sources only on public companies. We collected data from nine countries in the database to provide diversity in country characteristics: Belgium, Denmark, Finland, France, Germany, Norway, Poland, Sweden, and Switzerland. This provided data on 4,314,086 firm-year observations on 820,275 firms during the period.

Measures

Firm size: The size of the firm is measured as the log of the number of employees as defined by the data in Orbis. Growth rate is calculated in the specification by controlling for the lag of the employment size.

[6] The data used for this study is based on update number 116, dated October 15, 2013.

Training: The main independent variable capturing the change in the value of human capital - whether human capital rises or falls as people age in a given industry - is the average amount of training provided to employees in a given industry each year. The variable was used by Coff (1999) in his analysis of industry-level human capital characteristics as a strategic resource in acquisitions. We view this variable as capturing the extent to which employees develop industry-specific knowledge increasing their value over time, which we treat as a stable industry-level characteristic.

We use data from surveys from 1979 through 1998 to determine industry-human capital characteristics. In the surveys, the respondents are asked about recent jobs, which are classified into 3-digit SIC industries. During this period, the industry SIC listings were consistently reported as the classifications as of the 1980 definition. The specific question asked is the amount of time spent in training for that job in the last year. We collect these responses for each respondent for each year and take the average for each industry. Data are only available for respondents who were asked the question and worked in a given industry. This yielded estimates for 175 industries based on 5726 responses. This variable is log transformation as *ln(1+ training hours)*. The variable is an industry-level characteristic applied to every firm within the individual and is applied as a constant for every firm-year observation within the specific industry. Table 1 includes examples of the high and low training industries.

Education: The alternative independent variable to test the hypothesis is the average education of employees in the industry. It is the second variable that Coff (1999) used to test industry knowledge characteristics in his study. The variable is derived also derived from the NLSY survey. The respondents answered their years of education that can range from zero to 20 years. The variable represents the type of employees in the industry that can affect both starting conditions as well as aging characteristics. Table 2 includes example of the high and low education industries from the sample. Education is transformed as *ln(1+education)*.

*** Insert Tables 1-2 about here ***

Age: The age of the firm is calculated by the current date minus the founding date. We dropped firms with a founding date before 1950 as outliers in case the firm age does not accurately represent the activities of the firm today with such an age. Age is transformed as *ln(1+age)*.

Control Variables

We control for two country-level characteristics affecting the firm environment and growth potential.

GDP: The Gross Domestic Product of each country is determined for each industry. The GDP affects the economic environment in which the firms are acting. This is collected from the World Bank World Development Indicators (World Bank, 2013). The variable is log transformed for the regression.

Inflation: A second country-specific indicator of the economy is included as a control. We use it to capture country-level characteristics that affect firm growth. Inflation is again collected by the World Bank and is presented as the percentage change in the CPI index within that country.

Public: In the selection models, we use the dummy variable *public* as 0 (private), 1 (public) and 2 (branch), which could affect growth possibilities or desires. In Orbis, the data field is the "Legal Form" and is provided in those levels. The "branch" characteristic is provided for only a few firms in the database and is so classified if the BvD data collected tied the firm as a direct branch of another firm.[7]

Empirical Tests

The empirical tests are based on a widely used structural model of firm growth:

$$S_t = \alpha S_{t-1}^{\beta} A_{t-1}^{\theta} T^{\gamma} (e^{T*A})^{\phi}$$

Where S_t is the size (measured as employment) of a firm at time t, Where A_t is the age (in years) of a firm at time t, and T is the average training provided to employees in the firm's 3-digit SIC code. From the hypotheses, and prior research, we expect the following coefficients:

$\beta < 1$
firms grow more slowly as they get bigger

$\theta < 0$
firms grow more slowly as they age

$\gamma < 0$
firms in industries that train more grow resources more slowly

$\phi > 0$
growth is higher for older firms in higher-training industries

The linear estimation equation after taking logs of both sides yields the empirical model:

$$\ln(S_t) = \ln(\alpha) + \beta \ln(S_{t-1}) + \theta \ln(A_{t-1}) + \gamma \ln(T) + \phi A * T$$

[7] Removing the "branch" characteristic does not affect the results.

The model is similar to classic growth papers like Evans (1987a, b) and Dunne, Roberts, and Samuelson (1989). The empirical models performed are pooled OLS regressions, random effect panel regression, fixed effect panel regression, and Heckman Selection Models with pooled estimates.

RESULTS

Descriptive statistics and correlations are presented in Table 3. Table 4 provides the base theoretical models consistent with previous studies using pooled OLS regressions. We then add the two alternative key variables that are the focus of this paper (the human capital variable and the interaction of human capital and firm age), as well as additional time varying control variables.[8]

*** Insert Table 3 about here ***

Model 1 is a pooled OLS regression with standard errors clustered by firm. Unsurprisingly, the coefficient on lagged employment is near unity since employment levels show a great deal of inertia. Consistent with most prior studies, the coefficient is less than one indicating that larger firms grow more slowly. The coefficient on age is negative. This also corresponds with prior literature (Dunne et al., 1989; Evans, 1987a, b) which has generally found that older firms grow more slowly.

Model 2 includes the training variable in the pooled regression. The lagged employment coefficient is 0.96 and similar in subsequent models. Also in line with earlier models, the effect of firm age on growth is negative (coefficient of -0.022). The sign on training hours is negative

[8] Empirical growth rate models generally only include the variables of theoretical interest, leaving little precedent for the addition of pure control variables.

and significant at -0.007. Model 3 includes the interaction of training and age. Consistent with hypothesis 1, the effect of training on growth is negative (coefficient of -0.032) indicating that firms grow more slowly in industries where resources increase in value as they age. Consistent with hypothesis 2, the effect of the interaction between age and training on growth is positive (coefficient of 0.0001): older firms grow more rapidly in industries where older resources are more valuable.

Model 4 rebuilds the pooled regression with the alternative variable of years of education. Model 5 adds the interaction between education and firm age. In both models 4 and 5, the sign on the education variable is negative at -0.04 and -0.097, respectively. The interaction between education and age is positive and significant with 0.00028. This is consistent for both hypotheses 1 and 2 given the alternative measure of human capital also.

We then run robustness models with different specifications to account for the panel structure and selection possibilities in the data. These are presented in the appendix with Tables 4-6. In each model, the theoretical variables under consideration remain in the hypothesized directions.

*** Insert Table 4 about here ***

Table 4 presents both fixed and random effects (Models 6-9) to check for the possibility that the observed effects are caused by time-invariant firm characteristics. The fixed effects specification leads to considerable change in coefficients. The fall in the coefficient on the lagged dependent variable, in particular, suggests that the fixed-effects specification introduces substantial bias to this dynamic model (Nickell, 1981).[9] Including random effects, a compromise often adopted in

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[9] While we could estimate this model with GMM to deal with the dynamic model bias in 'large N, small T" panel, we have not done so because we cannot use that specification with later models including the time-invariant training variable.

prior research, has a relatively small influence on the coefficients. [10]

*** Insert Table 5-6 about here ***

Since our panel is subject to attrition, we also perform Heckman Selection Test models in Tables 5 and 6 for the training and education variables respectively. We perform a two-stage selection model, adding *public* as an additional selection variable finding that public firms are more likely to survive. The Heckman model is a pooled model where a probit on survival is tested in the first stage and the predictions are used to test for selection in the second stage. Firms with valid data through 2012, are characterized as "survivors" and the dependent variable is set to 1 for all observations of surviving firms. If the firm is in the sample but stops reporting data at some point before 2012, the firm survivor variable is set to 0. We have at most 11 years of data for any firm but the firms vary widely in age as many were founded before the sample period begins. 53% of the firms stop reporting data in 2011 or before[11]. The first stage tests survivorship and is shown and the Mills ratio lambda is included in the second stage for firm growth. The results of the Heckman Selection models are consistent with the prior models for our variables of interest, suggesting that the conclusions are not heavily influenced by attrition.

The conclusions from the full models are not significantly different given the different specifications for the theoretical variables under consideration. We will use model 3 to analyze the practical significance given the training variable. To do so, we analyzed the trajectory for a firm of average size (12 employees in year one) in an industry that is training at plus or minus

[10] Since the training hours is constant for a firm during the entire period, as it is assumed to be a characteristic of the industry rather than a moving value of specific training applied, we cannot run fixed effects or GMM models once the other independent variable is included.
[11] Based on their first data points, firms that do and do not survive are not qualitatively different. The age of the removed firms range from 0 to 61 years and the size ranges from 0 to 159,532 employees. The surviving firms range from 0 to 62 years and 0 to 536.731 in age and size, respectively.

one standard deviation from the average industry. Initially, an average firm in our sample in a low training industry will be growing 3% more per annum than a firm in a high training industry. The difference will slowly decline and after 14 years, the firm growth rate will have just reversed and the firm in the high training industry will be growing faster. By year 30, a firm in the high training industry will be more growing 2% faster per annum than a firm in the low training industry.

DISCUSSION

We have found evidence that the way resources age (becoming more or less valuable over time) influences the relationship between firm age and firm growth. This finding may help explain contrasting findings about the relationship between firm age, firm growth rates, and by extension firm survival (Evans, 1987a; Hannan, 1998).

Evidence that resource aging alters the growth paths of firms has important broader implications for broader patterns of industry dynamics and the mortality rates of firms (Hannan, 1998) . Recognizing that in some industries resource aging leads to low initial growth rates that tend to rise over time relative to the growth rates of other industries, may help us to explain situations in which we see survival advantages for older firms, decreasing industry entry and exit, and increasing concentration over time. In contrast, understanding why growth rates in other industries begin high but tend to slow down over time may help us to explain situations in which we see survival advantages for younger firms, continued high rates of entry and exit, and continued fragmentation of the industry.

We have touched on only a few possible ways in which the aging of a firm's resources affect firm dynamics, industry dynamics, and firm's strategies. Variables we have treated as exogenous, such as how long it takes for resources to mature and be disposed, may vary systematically across industries and may differ across firms as well. Similarly, pay policies, maintenance policies, R&D budgets, training practices, and organizational structures along with many other policies may affect the relative productivity of newer and older stocks as well as the amount of time that resources spend within the firm in higher or lower value states.

Factors affecting how well firms manage these dynamics are also of potentially great interest. To manage an organization with aging resources well requires a rich appreciation of: how value changes as the resources age; when these changes take place; other interdependent factors that constrain or encourage firm growth; basic stock flow physics (e.g., that new resources must rise first and that a firm's stock of older resources can continue to rise long after it stops acquiring new resources); the factors influencing how long resources spend in each state of the aging chain; multiple distinct kinds of resources with different aging profiles; and the incentives that managers need to manage and balance short-term against longer-term performance.

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Figure 1: Base model of aging resources

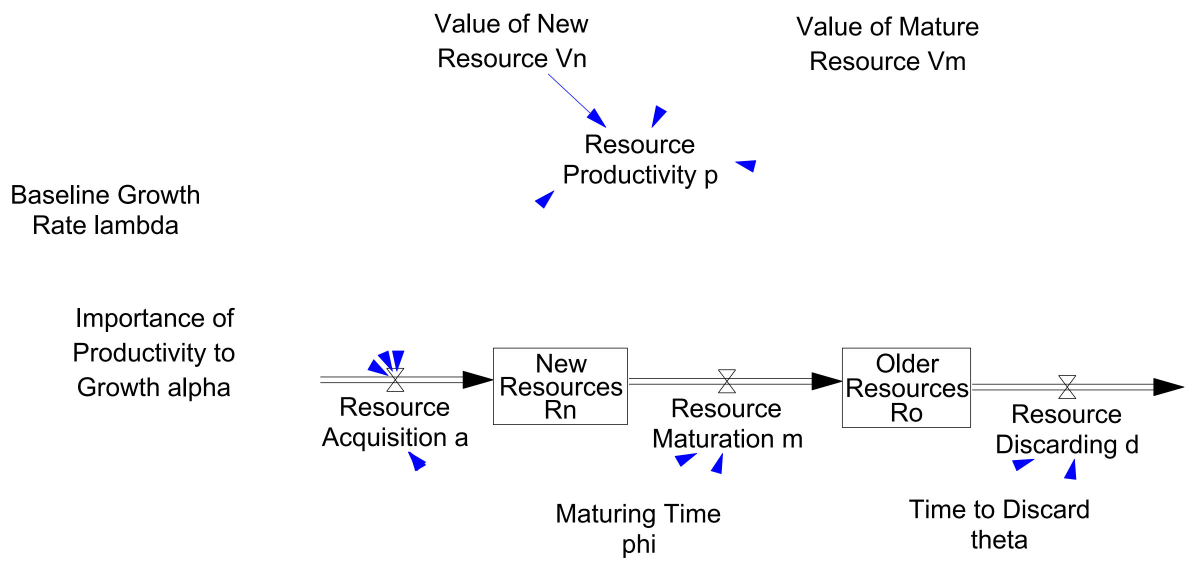


Figure 2: A firm's new resources must rise before older resources

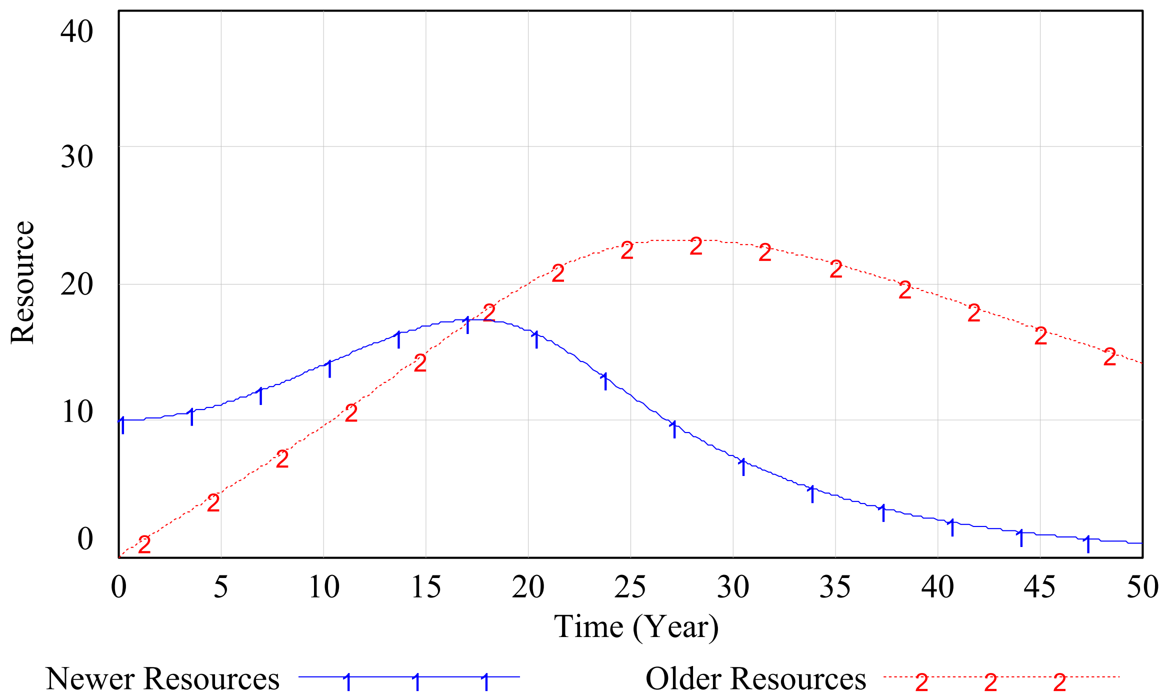
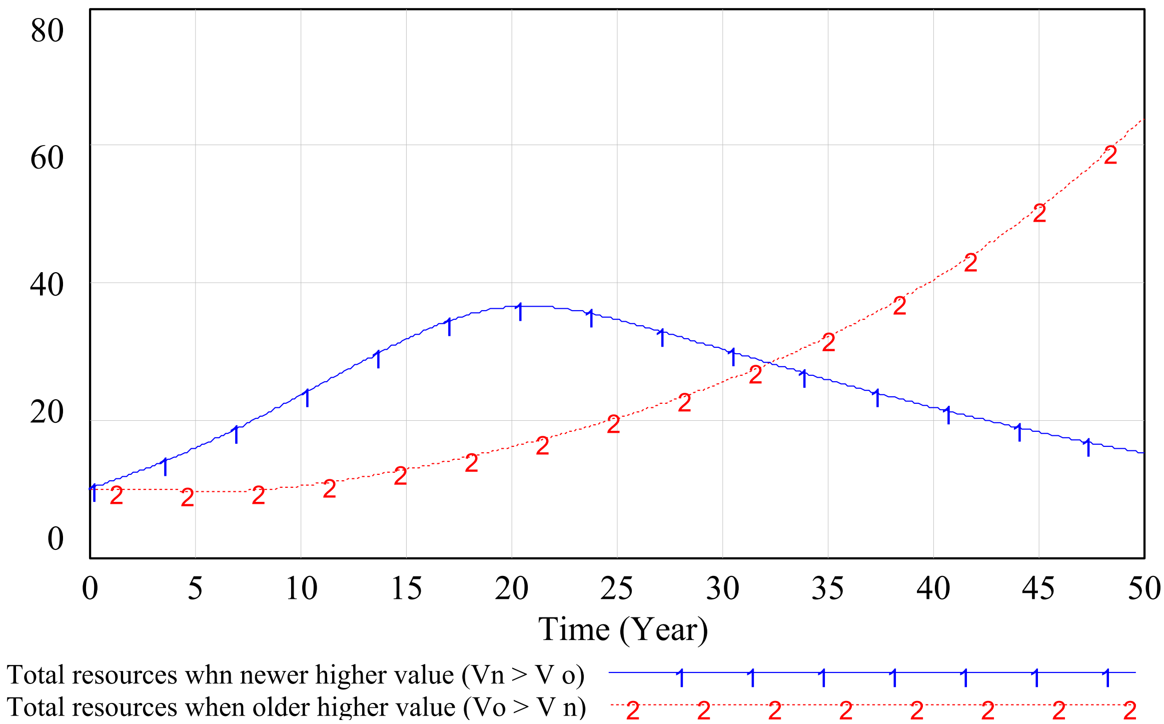


Figure 3: Firm growth as influenced by the relative value of new and older resources


80
60
40
20
0
0
5
10
15
20
25
30
35
40
45
50
Time (Year)
Total resources whn newer higher value (Vn > V o)
Total resources when older higher value (Vo > V n)

TABLES

Table 1: Example Industries with High and Low Training Hours

SIC3	Training Hours	Description
540	52.50	Paper and paper products
220	50.00	Leather tanning and finishing
420	45.00	Water transportation
379	40.00	Misc. Transportation Equipment
422	40.00	Pipe lines, except natural gas
781	40.00	MOTION PICTURE PRODUCTION AND ALLIED SERVICES
152	35.00	GENERAL BUILDING CONTRACTORS-RESIDENTIAL BUILDINGS
729	35.00	MISCELLANEOUS PERSONAL SERVICES
472	34.50	ARRANGEMENT OF PASSENGER TRANSPORTATION
551	8.33	MOTOR VEHICLE DEALERS (NEW AND USED)
161	7.57	HIGHWAY AND STREET CONSTRUCTION, EXCEPT ELEVATED HIGHWAYS
541	7.50	GROCERY STORES
737	7.50	COMPUTER PROGRAMMING, DATA PROCESSING, AND OTHER COMPUTER RELATED
478	6.00	MISCELLANEOUS SERVICES INCIDENTAL TO TRANSPORTATION
239	4.00	MISCELLANEOUS FABRICATED TEXTILE PRODUCTS
252	3.33	OFFICE FURNITURE
178	3.00	WATER WELL DRILLING
301	3.00	TIRES AND INNER TUBES
382	1.50	LABORATORY APPARATUS AND ANALYTICAL, OPTICAL, MEASURING, AND CONTR

Table 2: Example Industries with High and Low Education

SIC3	Education	Description
822	15.69	Colleges and Universities
841	14.80	Museums and Art Galleries
842	14.72	Botanical and Zoological Gardens
732	14.56	Credit Reporting and Collection
872	14.37	Accounting, Auditing, and Bookkeeping
921	14.36	Courts
178	11.20	WATER WELL DRILLING
781	11.17	MOTION PICTURE PRODUCTION AND ALLIED SERVICES
271	11.15	Newspapers
319	10.94	Leather Goods
679	10.82	Miscellaneous Investing
478	10.61	Miscellaneous Transportation Services
141	10.47	Dimension Stone
769	9.80	Misc. Repair Shops

Table 3: Descriptive Statistics

No.	Variable	Mean	Std. Dev	Min	Max	1	2	3	4	5	6	7
1	employment	37.91	1471.54	0.00	536731	1.0000						
2	age	13.44	11.31	0.00	63.00	0.0156	1.0000					
3	training hours	19.12	8.38	1.50	52.50	-0.0100	-0.0061	1.0000				
4	gdp	1.74E+12	1.26E+12	1.64E+11	3.62E+12	0.0063	0.0017	-0.0341	1.0000			
5	inflation	1.47	1.09	-0.67	4.49	0.0060	-0.0082	-0.0036	0.1919	1.0000		
6	public	0.17	0.38	0.00	2.00	0.0227	0.1976	-0.0382	-0.1088	-0.1725	1.0000	
7	education	12.58	0.96	9.80	15.69	-0.0030	0.0563	-0.0295	-0.0946	-0.0420	0.0490	1.0000

All correlations above ± .001 are significant at $p < 0.001$

Table 4: Pooled OLS Models

	Model 1		Model 2		Model 3		Model 4		Model 5	
Description	Base		Training		Interaction		Education		Interaction	
constant	-0.4167309	***	-0.3937723	***	-0.280291	***	-0.3072831	***	-0.0797904	***
std. error	0.0063377		0.0064841		0.0067179		0.0097637		0.0101548	
GDP	0.0189564	***	0.0188777	***	0.0187023	***	0.0187115	***	0.0181021	***
std. error	0.0002275		0.0002275		0.0002274		0.0002281		0.0002279	
inflation	0.0182591	***	0.0182645	***	0.0183863	***	0.0181804	***	0.0183502	***
std. error	0.0001889		0.0001889		0.0001887		0.0001889		0.0001887	
lagged employment	0.9641213	***	0.9639442	***	0.9635358	***	0.9639862	***	0.9635749	***
std. error	0.0001782		0.0001785		0.0001785		0.0001785		0.0001783	
age	-0.0219712	***	-0.0219065	***	-0.0482961	***	-0.0217036	***	-0.0695883	***
std. error	0.0002859		0.0002859		0.0005018		0.0002865		0.0006607	
training			-0.0072498	***	-0.0323121	***				
std. error			0.0004331		0.0005837					
age * training					0.0001026	***				
std. error					1.60E-06					
education							-0.0406837	***	-0.0973144	***
std. error							0.0027609		0.0028463	
age * education									0.0002816	***
std. error									3.50E-06	
Observations	2857518		2857518		2857518		2857518		2857518	
Adj R^2	0.9178		0.9178		0.9179		0.9178		0.918	

*** p-value < 0.001, ** p-value < 0.01, * p-value < 0.05

Appendix: Robustness Models

Table 5: Alternative Panel Specifications – training as key independent variable

	Model 6		Model 7		Model 8		Model 9	
Description	Fixed Effects		Random Effects		Random Effects		Random Effects	
constant	5.57282	***	-0.4971492	***	-0.4645265	***	-0.3430437	***
std. error	0.0754511		0.0081025		0.0083023		0.0085485	
gdp	-0.16741		0.0234966	***	0.0233576	***	0.0231027	***
std. error	0.0027971		0.0002912		0.0002912		0.0002906	
inflation	0.0191733		0.0167598	***	0.016764	***	0.0168815	***
std. error	0.0002315		0.0001928		0.0001928		0.0001927	
lagged employment	0.455595	***	0.9360372	***	0.9358329	***	0.9356784	***
std. error	0.0006504		0.0002284		0.0002287		0.0002283	
age	0.0468202	***	-0.0179349	***	-0.0178966	***	-0.0462325	***
std. error	0.0013768		0.0003491		0.0003491		0.0006048	
training					-0.0100189	***	-0.037044	***
std. error					0.0005569		0.0007295	
age * training							0.0001165	***
std. error							2.04E-06	
public								
std. error								
Mills Ratio (lambda)								
std. error								

*** p-value < 0.001, ** p-value < 0.01, * p-value < 0.05

Table 6: Alternative Specifications – training as key independent variable

	Model 10 - Heckman				Model 11 - Heckman				Model 12 - Heckman			
Description	1st Stage - survival		2nd Stage - size		1st Stage - survival		2nd Stage - size		1st Stage - survival		2nd Stage - size	
constant	23.26702	***	0.0811731		23.26647	***	0.1226454	**	23.46307	***	0.379146	***
std. error	0.025832		0.0413306		0.0264236		0.041415		0.0274938		0.0420958	
gdp	-0.8205811	***	-0.0000722		-0.8205792	***	-0.0006784		-0.8211663	***	-0.0051964	**
std. error	0.0009188		0.0015649		0.000919		0.0015653		0.0009195		0.0015749	
inflation	-0.167576	***	0.0202076	***	-0.1675757	***	0.0200938	***	-0.1676862	***	0.0193096	***
std. error	0.000809		0.0003702		0.000809		0.0003702		0.0008091		0.0003711	
lagged employment	-0.0407263	***	0.962056	***	-0.0407229	***	0.9618016	***	-0.0410745	***	0.9610741	***
std. error	0.0007271		0.0002383		0.0007279		0.0002389		0.0007283		0.0002393	
age	0.0522036	***	-0.0199589	***	0.0522023	***	-0.0197278	***	0.0084298	***	-0.0523417	***
std. error	0.0011596		0.0003949		0.0011597		0.0003951		0.0020275		0.0006629	
training					0.0001718		-0.0089427	***	-0.0415817	***	-0.0404567	***
std. error					0.0017493		0.0005735		0.0023616		0.0007805	
age * training									0.0001742	***	0.0001256	***
std. error									6.62E-06		2.10E-06	
public	0.3381056	***			0.3381171	***			0.3339433	***		
std. error	0.0024716				0.0024744				0.0024795			
Mills Ratio (lambda)			0.045424	***			0.0466993	***			0.0566444	***
std. error			0.0034951				0.003496				0.0035158	

*** p-value < 0.001, ** p-value < 0.01, * p-value < 0.05

Table 7: Alternative Specifications – education as key independent variable

	Model 13		Model 14		Model 15 - Heckman				Model 16 - Heckman			
Description	Random Effects		Random Effects		1st Stage - survival		2nd Stage - size		1st Stage - survival		2nd Stage - size	
constant	-0.3358303	***	-0.1020302	***	22.64383	***	0.1800559	***	22.96601	***	0.6105656	***
std. error	0.0125852		0.0129616		0.0396872		0.0412989		0.0413704		0.0423588	
gdp	0.0231341	***	0.0224418	***	-0.8192993	***	0.0002689		-0.8205071	***	-0.0062575	***
std. error	0.0002919		0.0002909		0.0009207		0.0015683		0.0009221		0.0015806	
inflation	0.016698	***	0.0168779	***	-0.1673368	***	0.0202264	***	-0.1674644	***	0.0192004	***
std. error	0.0001929		0.0001927		0.0008091		0.0003702		0.0008092		0.0003711	
lagged employment	0.9358676	***	0.9359228	***	-0.0399198	***	0.9618732	***	-0.0400606	***	0.9610892	***
std. error	0.0002286		0.0002278		0.0007282		0.0002386		0.0007285		0.0002388	
age	-0.0175665	***	-0.067201	***	0.0509797	***	-0.0196671	***	-0.0156955	***	-0.0783332	***
std. error	-0.0175665		0.0007826		0.0011612		0.0003948		0.0026582		0.0008748	
education	-0.0599783	***	-0.1190146	***	0.2328789	***	-0.0426113	***	0.1555642	***	-0.1109297	***
std. error	0.0035809		0.0036632		0.0112946		0.0035571		0.0116303		0.003659	
age * education			0.000309	***					0.0004	***	0.0003414	***
std. error			4.37E-06						1.43E-05		4.63E-06	
public					0.336263	***			0.3308672	***		
std. error					0.0024735				0.0024808			
Mills Ratio (lambda)							0.044056	***			0.0570325	***
std. error							0.0035084				0.0035316	

*** p-value < 0.001, ** p-value < 0.01, * p-value < 0.05