Appendix B: Online Materials for "Radical and Incremental Innovation: The Roles of Firms, Managers and Innovators"

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- Additional Graphs and Tables -

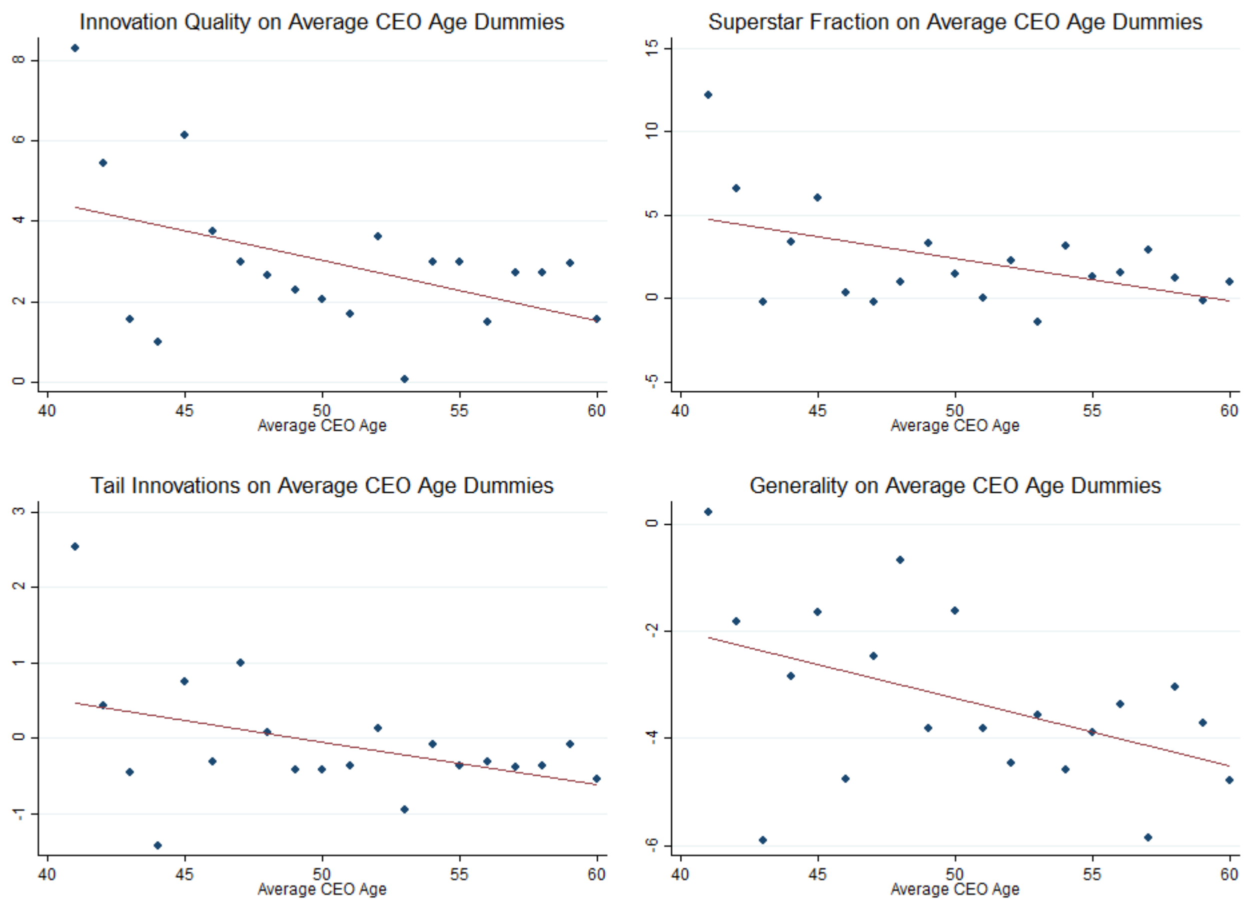

Figure B1: Estimated age dummies for the creative innovation variables (innovation quality, superstar fraction, tail innovations, and generality), and the associated fitted line. These figures repeat the regressions from Table 2, where CEO age is introduced as an array of discrete dummies instead of a linear regressor, and plot the estimated coefficients for the 21 age bins between ages of 40 and 60. The label 40 stands for all ages less than or equal to 40, and 60 stands for all ages greater than or equal to 60. See text and notes to Table 1 for variable definitions.

Table B1: Innovation Quality — Including Controls Incrementally

	Innovation Quality	Innovation Quality	Innovation Quality	Innovation Quality
CEO age	-0.172	-0.161	-0.176	-0.171
	(0.079)	(0.078)	(0.084)	(0.075)
log patent	-0.328	-0.080	-0.222	-0.364
	(0.187)	(0.294)	(0.298)	(0.294)
log employment		-0.335	-1.633	-1.172
		(0.353)	(0.884)	(0.852)
log sales			1.416	1.453
			(0.826)	(0.813)
firm age				-0.075
				(0.025)
N	7,170	7,170	7,170	7,170

Notes: Weighted firm-level panel regressions with annual observations with number of patents (in that year) as weights. The dependent variable is innovation quality. The key right-hand side variable is average CEO age (constant over time). Robust standard errors clustered at the firm level are in parentheses. A full set of four-digit SIC dummies, and year dummies (and thus no firm dummies) are included as controls. Different from the baseline specification in Table 2, we add the control variables incrementally. See text and notes to Table 1 for variable definitions.

Table B2: Cross-Sectional Regressions — Further Robustness

	Innovation Quality	Superstar Fraction	Tail Innovation	Generality
Panel A: Balanced Sample				
CEO age	-0.267	-0.295	-0.111	-0.185
	(0.092)	(0.140)	(0.042)	(0.053)
N	297	297	297	297
Panel B: With Average Manager Age				
average manager age	-0.267	-0.536	-0.113	-0.209
	(0.117)	(0.184)	(0.050)	(0.079)
N	7,170	7,170	7,170	6,286
Panel C: High-Tech Subsample				
CEO age	-0.147	-0.274	-0.083	-0.180
	(0.095)	(0.156)	(0.036)	(0.050)
N	2,100	2,100	2,100	1,901
Panel D: Low-Tech Subsample				
CEO age	-0.236	-0.422	-0.062	-0.155
	(0.090)	(0.121)	(0.030)	(0.079)
N	5,070	5,070	5,070	4,385
Panel E: Non-Pharmaceuticals Subsample				
CEO age	-0.157	-0.307	-0.077	-0.174
	(0.072)	(0.132)	(0.031)	(0.045)
N	6,662	6,662	6,662	5,860

Notes: Weighted firm-level panel regressions (without fixed effects) with annual observations with number of patents (in that year) as weights unless stated otherwise. The dependent variables are innovation quality, superstar fraction, tail innovation, and generality. The key right-hand side variable is average CEO age (constant over time). Each panel is for a different specification. Unless otherwise stated, all regressions control for firm age, log employment, log sales, log total patents, year dummies, and four-digit SIC dummies. Robust standard errors clustered at the firm level are in parentheses. Panel A displays a cross-sectional regression where all variables are the averages over the years 1995-2000 for a balanced sample of 279 firms. Panel B uses average manager age instead of CEO age. Panels C and D are for the high-tech and low-tech subsamples. High-tech subsample includes all firms with a primary industry classification of SIC 35 (industrial and commercial machinery and equipment and computer equipment) and 36 (electronic and other electrical equipment and components), while the low-tech subsample includes the rest. Panel E repeats the regression on Table 2 while dropping the pharmaceutical sector from the sample (SIC 283). See text and notes to Table 1 for variable definitions.

Table B3: Cross-Sectional Regressions Controlling for Recent Patent Flows

	Innovation Quality	Superstar Fraction	Tail Innovation	Generality
CEO age	-0.190	-0.335	-0.083	-0.167
	(0.084)	(0.134)	(0.033)	(0.043)
firm age	-0.074	-0.103	-0.016	-0.016
	(0.025)	(0.036)	(0.008)	(0.017)
log employment	-0.932	-2.065	-0.335	-1.200
	(0.805)	(1.172)	(0.242)	(0.654)
log sales	1.742	2.252	0.305	1.222
	(0.788)	(1.101)	(0.226)	(0.564)
log patent (3 yrs)	-0.957	-0.435	-0.017	0.063
	(0.312)	(0.542)	(0.086)	(0.232)
N	7,170	7,170	7,170	6,286

Notes: Weighted firm-level panel regressions with annual observations with number of patents (in that year) as weights. The dependent variables are innovation quality, superstar fraction, tail innovation, and generality. The key right-hand side variable is average CEO age (constant over time). Robust standard errors clustered at the firm level are in parentheses. A full set of four-digit SIC dummies, and year dummies (and thus no firm dummies) are included as controls. Different from the baseline specification in Table 2, we replace the log patent control variable with the natural logarithm of the patents created by the firm in the past three years. See text and notes to Table 1 for variable definitions.

Table B4: Cross-Sectional Regressions with Heckman Two-Step Estimation

	Innovation Quality	Superstar Fraction	Tail Innovation	Generality
CEO age	-0.087	-0.196	-0.039	-0.064
	(0.039)	(0.042)	(0.018)	(0.031)
	has any patents	has any patents	has any patents	has any patents
CEO age	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)
N	19,708	19,708	19,708	19,708

Notes: Heckman two-step estimation results for the cross-sectional regressions in Table 2. The dependent variables are innovation quality, superstar fraction, tail innovation, and generality. The key right-hand side variable is average CEO age (constant over time). The sample includes all Compustat firms regardless of whether they generate any patents. The selection criterion is whether a firm generated any patents in a given year. The control variables for the first stage are firm age, log employment, log sales, and R&D intensity. The control variables for the second stage are the same as in Table 2. See text and notes to Table 1 for variable definitions.

Table B5: Cross-Sectional Regressions — Time Since IPO $\geq$ 10 Years

	Innovation Quality	Superstar Fraction	Tail Innovation	Generality
CEO age	-0.192	-0.384	-0.081	-0.184
	(0.077)	(0.125)	(0.030)	(0.044)
N	5,303	5,303	5,303	4,639

Notes: Weighted firm-level panel regressions with annual observations with number of patents (in that year) as weights. The dependent variables are innovation quality, superstar fraction, tail innovation, and generality. The key right-hand side variable is average CEO age (constant over time). Robust standard errors clustered at the firm level are in parentheses. A full set of four-digit SIC dummies, and year dummies (and thus no firm dummies) are included as controls. Different from the baseline specification, we exclude observations if the firm's initial public offering is more recent than 10 years. See text and notes to Table 1 for variable definitions.

Table B6: Cross-Sectional Regressions — Alternative Measures

	Innovation Quality (5 years)	Superstar Fraction (Best Patent)	Tail Innovation (90/0)	Originality
	Panel A: Weighted			
CEO age	-0.103	-0.597	-0.161	-0.278
	(0.053)	(0.336)	(0.063)	(0.102)
N	4,606	7,170	7,170	7,150
	Panel B: Unweighted			
CEO age	-0.058	-0.260	-0.140	-0.036
	(0.045)	(0.097)	(0.068)	(0.052)
N	4,606	7,170	7,170	7,150

	Tail Innovation (99/50)	Employment Growth	Sales Growth	R&D Intensity
	Panel C: Weighted			
CEO age	-0.105	-0.120	-0.152	-5.366
	(0.045)	(0.137)	(0.130)	(9.626)
N	5,852	5,472	5,472	5,966
	Panel D: Unweighted			
CEO age	-0.070	-0.162	-0.193	-40.141
	(0.041)	(0.080)	(0.089)	(87.639)
N	5,852	5,472	5,472	5,966

	First Renewal	Second Renewal	Internal Innovation
	Panel E: Weighted		
CEO age	-0.259	-0.268	0.818
	(0.078)	(0.101)	(0.924)
N	7,170	7,170	7,150
	Panel F: Unweighted		
CEO age	-0.040	-0.145	0.279
	(0.067)	(0.094)	(0.398)
N	7,170	7,170	7,150

Notes: Firm-level panel regressions with annual observations with number of patents (in that year) as weights. The dependent variables in Panels A and B are alternative measures of innovation quality (computed over the next five years), superstar fraction (with superstars defined according to the best patent), tail innovation (with share of the patents of the firm among all the patents above the 90th percentile of the citation distribution in the numerator), and the originality index. The dependent variables in Panels C and D are measures of tail innovation (with fraction of patents above the median in the denominator), employment growth and sales growth, and R&D intensity. The dependent variables in Panels E and F are the fraction of patents that are renewed at least once (first renewal, due 4 years after patent grant), renewed at least twice (second renewal, due 8 years after patent grant), and the fraction of internal innovations where a patent is classified as an internal innovation if more than half of its backward citations are self-citations. The key right-hand side variable is average CEO age (constant over time). Robust standard errors clustered at the firm level are in parentheses. All regressions control for firm age, log employment, log sales, log total patents, year dummies and a full set of dummies for four-digit SIC industries. Regressions in Panel A and column 1 of Panel C are weighted by total patent count. Regressions in the last three columns of Panel C are weighted by firm employment. Regressions in Panels B and D are not weighted. See text and notes to Table 1 for variable definitions.

Table B7: Industry-Level Panel Regressions (SIC4)

	Innovation Quality	Superstar Fraction	Tail Innovation	Generality
CEO age	-0.271	-0.144	-0.039	-0.077
	(0.068)	(0.056)	(0.030)	(0.056)
N	2,369	2,369	2,369	2,178

Notes: Industry-level panel regressions with robust standard errors. The dependent variables are innovation quality, superstar fraction, tail innovation, and generality, which are calculated as the industry-level averages for the four-digit SIC industries in each year. The key right-hand side variable is the CEO age, which is calculated as the industry-level average for the four-digit SIC industries in each year. A full set of four-digit SIC dummies, and year dummies are included as controls. See text and notes to Table 1 for variable definitions.

Table B8: Panel Regressions (with Fixed Effects) — Further Robustness

	Innovation Quality	Superstar Fraction	Tail Innovation	Innovation Quality	Superstar Fraction	Tail Innovation
Panel A: No Covariates Except Time and Firm Fixed Effects						
CEO age	-0.244	-0.194	-0.059	-0.161	-0.124	-0.037
	(0.059)	(0.063)	(0.014)	(0.050)	(0.056)	(0.010)
lead CEO age				-0.163	-0.139	-0.042
				(0.054)	(0.046)	(0.016)
N	7,170	7,170	7,170	5,472	5,472	5,472
Panel B: With Additional Controls						
CEO age	-0.189	-0.152	-0.049	-0.118	-0.090	-0.030
	(0.045)	(0.051)	(0.012)	(0.044)	(0.049)	(0.011)
lead CEO age				-0.127	-0.115	-0.036
				(0.048)	(0.043)	(0.014)
N	7,139	7,139	7,139	5,457	5,457	5,457
Panel C: With Additional Controls Plus R&D Intensity						
CEO age	-0.188	-0.150	-0.048	-0.117	-0.089	-0.029
	(0.046)	(0.052)	(0.012)	(0.044)	(0.050)	(0.011)
lead CEO age				-0.128	-0.117	-0.036
				(0.049)	(0.044)	(0.014)
R&D intensity	0.175	-1.912	1.090	1.671	-2.255	1.489
	(2.790)	(2.206)	(0.927)	(3.187)	(2.893)	(1.045)
N	5,951	5,951	5,951	4,762	4,762	4,762
Panel D: Non-Pharmaceuticals Subsample						
CEO age	-0.190	-0.155	-0.049	-0.109	-0.087	-0.028
	(0.046)	(0.053)	(0.013)	(0.044)	(0.051)	(0.012)
lead CEO age				-0.146	-0.129	-0.039
				(0.051)	(0.046)	(0.015)
N	6,662	6,662	6,662	5,062	5,062	5,062
Panel E: Median Regression						
CEO age	-0.150	-0.103	-0.021	-0.127	-0.059	-0.018
	(0.013)	(0.044)	(0.008)	(0.008)	(0.063)	(0.008)
lead CEO age				-0.045	-0.067	-0.009
				(0.008)	(0.060)	(0.008)
N	7,170	7,170	7,170	5,472	5,472	5,472

Notes: Weighted firm-level panel regressions with annual observations with number of patents (in that year) as weights. The dependent variables are innovation quality, superstar fraction, and tail innovation. Robust standard errors clustered at the firm level are in parentheses. All specifications control for log employment, log sales, log patents, year dummies and a full set of firm fixed effects unless mentioned otherwise. Panel A repeats the regressions in Table 5 Panels B and E where all controls except year and firm fixed effects are dropped. Panel B repeats the same regressions while introducing the additional controls profitability, indebtedness and log physical capital. Panel C repeats the same regression as Panel B with the addition of R&D intensity as a control. Panel D repeats the same regressions while dropping the pharmaceuticals sector from the sample (SIC 283). Finally, Panel E reports the results of a median regression, where we first demean all observations to remove firm fixed effects. See text and notes to Table 1 for variable definitions.

Table B9: Panel Regressions (with Fixed Effects) — Alternative Measures

	Innovation Quality (5 years)	Superstar Fraction (Best Patent)	Tail Innovation (90/0)	Originality
	Panel A: Weighted			
CEO age	-0.067	-0.110	-0.212	-0.031
	(0.039)	(0.063)	(0.052)	(0.027)
N	4,606	7,170	7,170	7,150
	Panel B: Unweighted			
CEO age	-0.077	-0.092	-0.240	-0.041
	(0.055)	(0.053)	(0.057)	(0.041)
N	4,606	7,170	7,170	7,150

	Tail Innovation (99/50)	Employment Growth	Sales Growth	R&D Intensity
	Panel C: Weighted			
CEO age	-0.077	0.143	0.027	0.635
	(0.023)	(0.196)	(0.125)	(3.295)
N	5,852	5,472	5,472	5,966
	Panel D: Unweighted			
CEO age	-0.046	-0.043	0.008	148.017
	(0.036)	(0.075)	(0.089)	(121.754)
N	5,852	5,472	5,472	5,966

Notes: Firm-level panel regressions with annual observations with number of patents (in that year) as weights. The dependent variables in Panels A and B are alternative measures of innovation quality (computed over the next five years), superstar fraction (with superstars defined according to the best patent), tail innovation (with share of the patents of the firm among all the patents above the 90th percentile of the citation distribution in the numerator), and the originality index. The dependent variables in Panels C and D are measures of tail innovation (with fraction of patents above the median in the denominator), employment growth and sales growth, and R&D intensity. The key right-hand side variable is CEO age. Robust standard errors clustered at the firm level are in parentheses. All regressions control for log employment, log sales, log total patents, year and firm dummies. Regressions in Panel A and column 1 of Panel C are weighted by total patent count. Regressions in columns 2-4 of Panel C are weighted by firm employment. Regressions in Panels B and D are not weighted. See text and notes to Table 1 for variable definitions.

Table B10: Continuing Inventors vs New Hires — Innovation Quality

	Innovation Quality (All)	Innovation Quality (New Inventors)	Innovation Quality (Continuing Inventors)
CEO age	-0.190	-0.207	-0.161
	(0.044)	(0.045)	(0.042)
N	7,170	5,818	5,584
mean of dep. var.	15.9	16.9	17.4

Notes: Weighted firm-level panel regressions with annual observations with number of patents (in that year) as weights. The dependent variables is the innovation quality measure calculated in three different ways. The first column uses the information from all the patents of a firm. The second column uses the information only from patents created by new inventors, where a new inventor is defined as an inventor who has never worked for the particular firm before. The third column uses the information only from patents created by continuing inventors. When a patent is created by a mix of new and continuing inventors, it is weighted according to the fraction of new vs. continuing inventors, defined as the inverse of a new inventor. The key right-hand side variable is CEO age. Robust standard errors clustered at the firm level are in parentheses. All specifications control for log employment, log sales, log patents, year dummies and a full set of firm fixed effects (and thus firm age and the four-digit SIC dummies are no longer included). See text and notes to Table 1 for variable definitions.

Table B11: Continuing Inventors vs New Hires — Tail Innovations

	Tail Innovations (All)	Tail Innovations (New Inventors)	Tail Innovations (Continuing Inventors)
CEO age	-0.049	-0.052	-0.035
	(0.012)	(0.020)	(0.023)
N	7,170	5,818	5,584
mean of dep. var	1.71	1.89	2.06

Notes: Weighted firm-level panel regressions with annual observations with number of patents (in that year) as weights. The dependent variables is the tail innovation measure calculated in three different ways. The first column uses the information from all the patents of a firm. The second column uses the information only from patents created by new inventors, where a new inventor is defined as an inventor who has never worked for the particular firm before. The third column uses the information only from patents created by continuing inventors. When a patent is created by a mix of new and continuing inventors, it is weighted according to the fraction of new vs. continuing inventors, defined as the inverse of a new inventor. The key right-hand side variable is CEO age. Robust standard errors clustered at the firm level are in parentheses. All specifications control for log employment, log sales, log patents, year dummies and a full set of firm fixed effects (and thus firm age and the four-digit SIC dummies are no longer included). See text and notes to Table 1 for variable definitions.

- Discussion of Assumptions and Microfoundations -

In this subsection, we discuss the role and possible microfoundations of the critical assumption underpinning the assignment of young managers to high-type firms and to radical innovation—the comparative advantage in equation (5).

Endogenizing human capital decisions: Our key justification for (5) is that agents acquire the knowledge available at the time they are born. Though this was imposed as a technological feature, it can be readily endogenized (as in Chari and Hopenhayn, 1993, or MacDonald and Weisbach, 2004). The most natural assumption here would be that agents decide when to go to school, and an agent who goes to school for some prespecified period of time, say an interval of length $\Delta > 0$, and graduates at time t acquires the frontier knowledge at that time, q_t as given in (3). Given the stationary structure of the problem, we can make two observations. First, it is always optimal for an agent to acquire schooling immediately (rather than wait and do so at a later date).[1] Second, we can also derive a straightforward sufficient condition ensuring that an agent would never want to go back to school after this initial schooling interval. In particular, once again starting in stationary equilibrium, if a manager of age a at time t does not go back to school, she will have a discounted lifetime income of

$$\int_0^\infty e^{-(r+\delta)s}[\bar{q}_{t+s}f(a+s) + \max\left\{\Lambda\theta_H\left[\bar{q}^{a+s} - \bar{q}^{a^*}\right], 0\right\}\mathbb{E}V_H(\bar{q}_{t+s})]ds, \tag{B1}$$

while if she goes back to school, her discounted lifetime income will be

$$\int_\Delta^\infty e^{-(r+\delta)s}[\bar{q}_{t+s}f(a+s) + \max\left\{\Lambda\theta_H\left[\bar{q}^{s} - \bar{q}^{a^*}\right], 0\right\}\mathbb{E}V_H(\bar{q}_{t+s})]ds. \tag{B2}$$

The latter expression thus enables the agent to reduce $\bar{q}^a$ and potentially earn more from being assigned to high-type firms.[2] However, its comparison to the previous expression makes it clear that if $f(a)$ and Δ are sufficiently large, then it will not be beneficial for a manager to go back to school. For example, an upper bound for the discounted lifetime income from schooling is

$$\int_\Delta^\infty e^{-(r+\delta)s}\bar{q}_{t+s}f(a+s) + \Lambda\theta_H\left[1 - \bar{q}^{a^*}\right]\mathbb{E}V_H(\bar{q}_{t+s})]ds = \int_\Delta^\infty e^{-(r+\delta)s}\bar{q}_{t+s}f(a+s)\,ds + \frac{\bar{q}_t\Lambda\theta_H\left[1 - \bar{q}^{a^*}\right]}{r+\delta-g}e^{-\Delta(r+\delta-g)}, \tag{B3}$$

which assumes that after re-schooling the manager has the highest contribution to innovation forever (whereas in reality her contribution would decline as she ages). On the other hand, the minimum lifetime incomes she would obtain without going to school can be written as

$$\int_0^\Delta e^{-(r+\delta)s}[\bar{q}_{t+s}\inf f(a)]ds + \int_\Delta^\infty e^{-(r+\delta)s}\bar{q}_{t+s}f(a+s)\,ds = \int_\Delta^\infty e^{-(r+\delta)s}\bar{q}_{t+s}f(a+s)\,ds + \frac{1 - e^{-(r+\delta-g)\Delta}}{r+\delta-g}\bar{q}_t f_{\min}, \tag{B4}$$

where $f_{\min} = \inf f(a)$. By comparing these two expressions and noting that their first terms are identical, we obtain a sufficient condition for any manager to never prefer to go back to school,

$$\Lambda\theta_H\left[1 - \bar{q}^{a^*}\right] < e^{\Delta(r+\delta-g)}f_{\min}. \tag{B5}$$

As already anticipated, this condition is satisfied when Δ or when $f_{\min}$ are large.

[1] This is because the problem facing an agent at any two dates is identical given the stationary environment and the constant probability of death, δ, and thus if the agent wanted to wait between time t and t', then she would also want to wait indefinitely, violating the transversality condition.

[2] Notice that in writing these expressions, we are interpreting a literally as age, so that when the manager goes back to school, her age is not affected. Alternatively, a could stand for the manager's experience in a particular line of business, and in that case, a could also be reset when she goes back to schooling, which would introduce an additional opportunity cost of returning to school. This does not have an important effect on the qualitative argument here, though it may provide a better approximation to some applications.

An alternative form of comparative advantage: We introduced the comparative advantage of young managers in radical innovation in the simplest possible form—by assuming that they have the same productivity in incremental innovation and greater productivity in radical innovation. Similar results would obtain as well if they have comparable productivity in radical innovation but *lower productivity* in incremental innovation.

Suppose, for example, that all managers have the same rate of arrival of radical innovations given by $\Lambda\theta_H$ when they are employed by high-type firms, but the productivity of a manager aged a in incremental innovation is $\xi g(a)$, where $g(a)$ is increasing. In this case, the pattern of assignment will be slightly different—it will be first the older managers who are assigned to management, but there will still exist a critical age threshold, say a^{**}, such that managers younger than this age will be assigned to high-type firms wishing to specialize in radical innovation. Young managers will also earn strictly less than older managers, but radical innovations will continue to increase following a switch from older to younger managers.

Comparative advantage from competing uses of time: Relatedly, in our baseline model, radical innovations and the operational duties of a manager do not crowd each other out. An alternative, equally natural assumption is that, because seeking radical innovations is time-consuming, it will interfere with the cost-reducing activities of the manager. Under the natural and common assumption that all of these tasks have to be performed by a single manager (i.e., it is not possible to add a separate manager for innovations), attempting radical innovations will have the opportunity cost of reducing the other beneficial roles of the manager. Since experienced managers are more productive at cost reduction and other operational roles, this reasoning directly implies that it will be younger managers who have an effective comparative advantage in radical innovations, even if they are less productive in both operations and radical innovations than older managers.

A re-combinatorial microfoundation for comparative advantage: Another microfoundation for this pattern of comparative advantage is to assume that radical innovation requires recombining different ideas, while more experienced managers will have an expertise in exploiting a specific set of well-established ideas (perhaps ideas with which they have worked before). Such a microfoundation can be developed in a way that generates the pattern of comparative advantage in our baseline model.

One advantage of this alternative line is that the reason why more experienced managers are better at operations, but not as good as young managers in radical innovations, can be endogenized. Specifically, managers may choose to invest in their ability to understand and exploit certain technologies as they age, but this could be at the expense of remaining on top of other ideas, while younger managers may be "jacks of all trades, masters of none," making them less effective in running an established business, and as a result, giving them a comparative advantage in radical innovation.

An organizational microfoundation for comparative advantage: Yet another possibility leading to the pattern of matching in our model would come not from an intrinsic comparative advantage of young managers for radical innovation, but from the potential conflict of interest between managers and owners. Suppose that attempting radical innovation is more costly for managers, and it is difficult for the owners of the firm to verify that the manager is truly attempting radical innovations. This sort of situation will create a major conflict of interest, whereby all managers might wish to claim that they are attempting radical innovations, but in reality may shirk and go for the easy life. If, as it seems plausible, more experienced managers are better able to control the flow of information out of an organization and thus hide their true activities, it might be more difficult for owners to induce these experienced managers to engage in radical innovation. It may then be cheaper and more effective to turn to more "pliable" younger managers when there will be a switch to radical innovation.

Finite lives and risk-taking: The comparative advantage of younger managers in more radical innovations may also come from their greater willingness to take risks, which could in turn have biological roots or may be a consequence of the fact that, when lives are finite, they will have longer horizon than older managers and thus tend to have greater tolerance for risk.

Managers and inventors: We have so far abstracted from inventors, which play an important role both in practice and in our data analysis below. A final alternative structure which leads to similar results is to assume that it is not young managers who are important for radical innovation, but young inventors (a pattern for which we also find support in the data). But if young inventors work better in a team with young managers, for example because older managers would not communicate well with them or would attempt to block some of their ideas, there will again be a pattern in which young managers are assigned to firms specializing in radical innovations.