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ABSTRACT

What determines firm growth over the life-cycle? Exploiting unique firm panel data on internal organization, balance sheets and innovation, representative of the entire Canadian economy, we study recent theories that examine life-cycle patterns for firm growth. These theories include organizational capital accumulation and management practices, financial frictions, learning about demand, and recent endogenous growth models with incumbent innovation. We emphasize the importance of differentiating between pure age effects of these theories and effects on size conditional on age. Our stylized facts highlight both empirical successes and shortcomings of current theory. First, models of organizational capital and innovation are broadly consistent with firm size correlations conditional on age but have difficulties matching the life-cycle dynamics of firm organization and innovation. Second, among theories we analyze, organizational capital and management practices are the most important determinants to explain intensive margin firm growth over the life-cycle. Third, although less important to explain intensive margin firm growth, financial frictions are an important determinant of firm exit, conditional on firm age.

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1 Introduction

A large empirical literature has documented important age effects in firm growth and exit patterns.[1] Moreover, recent empirical evidence suggests that these age dynamics are crucial for understanding aggregate outcomes. For instance, firm age dynamics account for a major part of employment growth, as shown by Haltiwanger, Jarmin and Miranda (2013), while Hsieh and Klenow (2014) argue that they are also important for understanding cross-country differences in aggregate productivity. Not surprisingly, a large theoretical literature has proposed a variety of mechanisms to relate firm outcomes to age effects, such as organizational capital accumulation, financial frictions, learning about demand, and innovation. Although these theories are successful in capturing firm growth patterns over the life-cycle, empirical evidence of the validity of these models remains rare.

In this paper, we assess those theories in a unified empirical framework by estimating new reduced-form moments that are informative for those theories, using a representative sample of Canadian establishments.[2] More specifically, we construct variables capturing the main mechanism of those theories of firm life-cycle dynamics and provide stylized facts that highlight both empirical successes and shortcomings of current theories. Our approach emphasizes the distinction between age and size effects both in our survey of the theoretical literature as well as in our empirical analysis, as suggested by recent studies such as Fort, Haltiwanger, Jarmin and Miranda (2013). Indeed, the firm life-cycle dynamics of many models are driven by the fact that older firms are typically larger and not necessarily by the fact that older firms have been active for a longer time span. Size effects, in other words, describe mechanisms through which young firms should run into the same scale effects as old firms of comparable size. We identify the most important mechanisms explaining firm dynamics suggested by recent theoretical contributions and determine whether they mainly operate through size or age effects, or both.[3] Since we construct direct proxies for the mechanisms in recent models of firm life-cycle dynamics, we will be able to distinguish age dynamics from size effects.

To our knowledge, this is the first empirical study to systematically construct proxy variables for a wide range of firm life-cycle theories and to contrast age dynamics and size effects of these theories in the data. This empirical progress is made possible by the availability of a relatively long firm panel dataset with com-

[1] See for example the empirical facts provided by Dunne, Roberts and Samuelson (1989) and the survey by Sutton (1997).

[2] More than 90% of businesses in our data are single-establishment firms. Unless noted otherwise, we therefore use the terms “establishment” and “firm” interchangeably, and we include a multi-establishment indicator in all our empirical analysis.

[3] Our selection of theoretical mechanisms is necessarily incomplete and partly driven by the necessity to map the theory to our data, although we believe that we cover the most important mechanisms.

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prehensive information on internal organization, balance sheets and innovation. In contrast to other studies in the literature, our data is representative of the entire Canadian economy—including the large service sector—and does not only capture specific industries such as manufacturing or pharmaceuticals.

We construct measures of mechanisms at the heart of four classes of firm life-cycle theories. First, we measure firm organization as emphasized in recent models of organizational capital accumulation such as Garicano and Rossi-Hansberg (2012) and Akcigit, Alp and Peters (2014) as well as management practices as highlighted by recent empirical work such as Bloom, Sadun and Van Reenen (2012) and Bloom, Eifert, McKenzie, Mahajan and Roberts (2013a). Second, variables such as financial leverage and term structure of debt capture main mechanisms of theories of financial frictions and firm dynamics as in Cooley and Quadrini (2001). Third, dynamic mark-ups play a crucial role in "learning about demand" as in Foster, Haltiwanger and Syverson (2013). Fourth, we measure innovation activity as emphasized by models of endogenous growth with incumbent innovation as in Klette and Kortum (2004).

We highlight a key set of findings that are informative for these theories of firm life-cycle dynamics. First, models with organizational capital accumulation such as Garicano and Rossi-Hansberg (2012) and models of endogenous innovation such as Klette and Kortum (2004) predict that the number of organizational layers and the likelihood to innovate increase monotonically as firms grow. While the age profiles of our theory-driven measures of organizational layers and innovation do not increase monotonically, these theories perform much better when we analyze size correlations controlling for firm age, which is the relevant statistic implied by those models. For instance, larger firms have systematically more organizational layers as predicted by Garicano and Rossi-Hansberg (2012).[4] Similarly, larger firms are also systematically more likely to innovate conditional on age as predicted by Klette and Kortum (2004). We argue both that this contrast between age and size effects is important to take into account in empirical work and that it can be fruitful for further theory development. Similarly, when analyzing size effects, we find support for the few theories that differentiate between product and process innovations, such as Klepper (1996). Consistent with those models, we find that larger firms tend to innovate and improve processes instead of products. However, in contrast to theoretical predictions, the likelihood of product and process innovations is systematically declining with age. Our results suggest that examining the emergence of precess and product innovations within firms is likely to be a fruitful area for future research.

Second, models of optimal delegation of real decision authority can have very different life-cycle predictions. For instance, if information acquired by employees becomes more important in larger firms, then theories of optimal delegation such as Aghion and Tirole (1997) would predict that firms decentralize decision-making as

[4] This result is also consistent with recent findings by Caliendo, Monte and Rossi-Hansberg (2014), who use a measure of organizational layers that is slightly different than ours.

they grow. On the other hand, stricter monitoring and centralization of decisions is the optimal response to firm growth in recent models such as Akcigit et al. (2014). While the life-cycle profile of our centralization measure does not offer uniform support for either mechanism, the more relevant effect on size conditional on age strongly supports models like Aghion and Tirole (1997).

Third, performance pay can be adopted to counter increased moral hazard arising from hiring more employees. In addition to this conditional size effect, Holmstrom (1989) conjectures that small firms focus on hard-to-monitor tasks such as innovation, while large firms need to mix innovation tasks with routine tasks such as production and distribution. One implication from a changing composition of tasks at firms could be that younger firms are more likely to adopt performance pay since they specialize in innovation, while older firms do not implement performance pay since a larger fraction of their tasks are easier to monitor than innovation. We find support for both channels in the data. The life-cycle profile of performance pay adoption is indeed downward sloping, and we also estimate an economically and statistically significant positive size effect conditional on firm age.

Fourth, we find evidence complementary to recent work on management practices by Bloom and Van Reenen (2007), which links management practices to firm productivity. In particular, firms are more likely to hire professional managers as they grow in size, which might either reflect the causal effect on firm performance from hiring professional managers who implement better management practices, or it could reflect the fact that larger firms are more likely to pay a fixed cost to implement professional management. In this context, an additional analysis of age profiles becomes instructive, since recent empirical evidence by Bloom et al. (2013a) has identified an additional age effect via learning about structured management. We find strong support for the learning channel and size effects of implementing professionalized management. The life-cycle profile of adopting professional management is strongly monotonically increasing, while we also find a large and significant size effect conditional on age.

Fifth, our analysis of firms' decision to outsource tasks speaks to theories of firm boundaries such as Williamson (1975) and Grossman and Hart (1986). Centering on relationship-specific investments as the main source of frictions generates the prediction that firms can reduce hold up problem by supplier diversification or by learning how to standardize inputs. Both channels imply that firms outsource more activities as they age and grow. We find strong evidence for this mechanism in the data, which shows a steeply increasing age profile as well as significant size effects of outsourcing, conditional on age.

Sixth, we find mixed evidence for models of financial frictions and firm growth. While the estimated life-cycle profile of leverage is flat, consistent with models such as Buera (2009) and Moll (2014), the positive size effect conditional on age is inconsistent with dynamic models of costly debt financing such as Cooley and Quadrini

(2001). At the same time, we find that financial frictions are important for explaining the extensive margin. While financial variables capturing financial frictions such as leverage and the maturity of firm debt are relatively unimportant in explaining intensive margin firm growth, they turn out to be the most important predictors of firm exit once we control for firm age. We therefore conclude that our results support theories of financial frictions that primarily focus on extensive margin effects, and that there is a need for both new theory explaining the positive relation between the intensive margin and leverage as well as for more empirical analysis of the effect of financial frictions on the intensive margin of firm growth.

Seventh, recent work by Foster et al. (2013) stresses the importance of pure age effects via a learning about demand channel in which young firms accumulate a customer basis by initially choosing low mark-ups when young before gradually increasing them with increased demand for their products. We do find support for this mechanism, as the life-cycle profile of mark-ups is indeed upward sloping. This is an important extension to Foster et al. (2013), since our data covers the entire economy and not only a few manufacturing industries with homogeneous, commodity-like goods.

Finally, we investigate which theory is most important for explaining firm life-cycle dynamics. We include our proxies for the various theories in a non-parametric regression of firm size including a full set of age effects as well as additional controls. We find that measures of organizational capital or management practices are the most important determinants of firm life-cycle dynamics conditional on firm survival. As mentioned before, financial frictions in turn are the most important predictors of firm exit conditional on age. However, while we find strong support for many theories, we also document that a large part of firm growth over the life-cycle as well as firm death still remains unexplained, even after controlling for all proxies of firm life-cycle theories. Much more research on the determinants of the life-cycle pattern of firm growth is need.

The paper is organized as follows. Section 2 reviews recent theories of firm life-cycle dynamics, which will guide our measurement and empirical analysis. We emphasize whether the main mechanism at the heart of different firm life-cycle theories is operating mainly through firm size or indeed firm age effects. Section 3 lays out the framework of our empirical approach, describing data sources and the baseline econometric model employed. We also compare our baseline results on firm growth over the life-cycle with empirical studies of the same age effects in other countries. Section 4 discusses the estimated age profiles and size effects conditional on firm age on the sample of surviving firms in the context of the models discussed in section 2 and using the methodology outlined in section 3. To facilitate exposition, we discuss the detailed construction of proxy variables right before presenting the results in this section. Section 5 discusses our results for the extensive margin. Section 6 concludes.

2 Theories of Firm Life-Cycle Dynamics

As background for our empirical analysis, we start by providing an overview of recent theories of firm age dynamics. As such, this review extends Atkeson and Kehoe (2005), who describe life-cycle dynamics of plants in US manufacturing and use this data to quantify the aggregate importance of organizational capital. In contrast to Atkeson and Kehoe (2005), we focus on theories of the actual mechanisms behind the accumulation of organizational capital. This review is not intended to be comprehensive, but will rather reflect availability of direct measures of these theories in our data.

One can roughly classify these theories into two groups, which are not mutually exclusive. The first set of theories centers around constraints to firm growth and the way firms overcome these constraints as they accumulate organizational or physical capital. This class of explanations includes theories of changes in firms' organizational or management practices, which center around internal firm constraints. More broadly, it also includes models of financial frictions in which firms overcome external constraints over time. The second set of theories of firm age dynamics focus on active knowledge accumulation at firms. These theories include models of firms' "learning about demand" as well as models of endogenous innovation.

Throughout our review, we will emphasize the difference between pure age effects and size effects. For the latter, the current size of a firm should be a sufficient statistic to predict what type of constraints to growth the firm is facing. In contrast, pure age effects require information beyond current size and are often related to learning mechanisms.

2.1 Firm Organization and Management Practices

Most firms start out as small organizations in which ownership and control are unified in the person of an entrepreneur. However, entrepreneurial firms eventually run into internal diseconomies of scale and therefore have to reorganize to sustain a larger firm size. This is a key idea of models relating firm age dynamics to internal firm organization and management practices. While early elaborations of this idea in Penrose (1959) or Lucas (1978) rely on unspecified "scarce managerial inputs" or "limited span of control," the recent literature analyzes the role of reorganization in helping to sustain a larger firm size.

Decision layers A natural source of diseconomies of scale is the business owner's time constraint as in Garicano (2000) and Garicano and Rossi-Hansberg (2012). In these models, a firm economizes on the business owner's time by introducing division of labor across organizational layers within the firm. Lower layers solve simple problems and report more complicated problems to higher layers, which in turn specialize in solving only complex problems. Garicano and Rossi-Hansberg (2012) describes a dynamic equilibrium model of exploration of new ideas and the exploitation of profits associated with existing ideas. When new technologies are first introduced or firms are founded, only the solution to the most common problems is known. Over time, as the organization faces more and more issues related to the commercialization of the new technology, managers learn more about complex problems and the firm adds more organizational layers. This addition of layers requires "time to build organizations," which is why the model in Garicano and Rossi-Hansberg (2012) introduces an age effect that is separate from the size effect due to the diseconomies of scale. An important prediction from this class of models is that the number of organizational layers increases over time as firms age and get larger, reflecting deeper knowledge specialization and division of labor.

Centralization A second form of internal constraints to growth is the presence of decentralized information. As a firm grows larger, employees hired by the business owner are likely to acquire knowledge during the conduct of day-to-day operations delegated to them. Since the business owner does not naturally have access to the same knowledge, decisions in larger firms can be based on worse information. To exploit this information, firms can decentralize decision making as emphasized by Aghion and Tirole (1997), thereby trading off the loss of control by the business owner against the utilization of information acquired by their employees. Because this type of information might become more important as firms get larger, the prediction would be that firms tend to decentralize as they grow in size. In contrast, recent work by Akcigit et al. (2014) focuses on the opposite site of this trade-off. As firms get larger, employees need to be monitored since they otherwise abuse their decision authority for personal gain. Akcigit et al. (2014) show that this leads to the prediction that firms should optimally centralize decision making as they grow. It is important to note that the mechanisms of both Aghion and Tirole (1997) and Akcigit et al. (2014) are in effect operating primarily through firm size instead of firm age.

Performance pay A third internal constraint to growth is moral hazard when hiring employees. To counter these moral hazard problems, firms can adopt performance pay to induce efficient decision making. Whether performance pay at firms is adopted early or late in the firm life-cycle depends on several factors. First, larger and older firms might naturally be subject to more moral hazard problems, since it is harder for business owners to monitor a large number of employees. A first prediction might therefore be that adoption of performance pay is more likely for old firms, which also tend to be larger. This first mechanism primarily operates through firm size, so that one might expect it applies also to young but large firms. Second, the composition of tasks conducted by employees might change over time. Harder-to-monitor tasks such as innovation and creative activities as in Holmstrom (1989) might be more important for younger firms, while older firms might focus more on relatively standardized tasks associated with the production and distribution of their established products. In this alternative view, performance pay adoption is more likely for young firms than for older firms. Since the task composition in this theory is a function of firm age and not primarily of size, the prediction that younger firms might be more likely to adopt performance pay is a pure age effect.

Presence of professional management An alternative way to deal with moral hazard of employees in large firms is to hire managers to monitor employees or to implement structured management practices that allow the implementation of a more effective employee incentive system. Theories of hierarchies as an optimal response to moral hazard issues as surveyed by Mukherjee (2012) predict that hiring of professional managers becomes more likely as firms expand in size. Similar to the implementation of performance pay, the introduction of managerial hierarchies in response to moral hazard can be considered a size effect. The predictions of this monitoring view of management are qualitatively similar to theories of the optimal implementation of management practices, as emphasized in work by Bloom and Van Reenen (2007) and Bloom et al. (2013a). In particular, we have two distinct mechanisms in mind.

First, firms that implement structured management practices might become more efficient, as shown by Bloom et al. (2013a). In this view, the correlation of size and the presence of professional management would reflect a causal effect of management on firm size. Second, implementing structured management practices might require a fixed cost so that only large firms hire professional managers to implement these practices. In this view, similar to the moral hazard view of managerial hierarchies, the installation of professional management is primarily driven by firm size.

A complementary view to these size effects is presented by learning mechanisms emphasized in the empirical work of Bloom et al. (2013a). As firms age, their owners learn about more structured management practices and hire professional managers to implement them. This last mechanism captures an age effect that is going beyond the firm size effects discussed before.

Outsourcing A final potential form of internal diseconomies of scale are customized activities that require firm-specific investments, which make firms vulnerable to hold up problems as in Williamson (1975) and Grossman and Hart (1986). In contrast to the factors analyzed thus far, firms might eventually be able to grow out of these constraints. The idea is that young firms start with many customized and firm-specific labor services or intermediates and therefore face severe inefficiencies implied by corresponding hold up problems. However, as firms age and standardize most of their activities, these inputs are more likely to be available in spot markets.

Older firms are therefore more likely to outsource activities and purchase labor services or intermediate inputs from other firms instead of providing them in-house. Note that this firm boundary mechanism might potentially be both a size and an age effect. On the one hand, it is potentially a size effect since higher demand by large firms is more likely to support multiple suppliers, which then mitigates hold up problems and makes outsourcing more likely. On the other hand, it can be an age effect since standardization might require time to optimally redesign the value chain inside the firm as well as time for suppliers to learn how to produce intermediates.

2.2 Financial Frictions

While the analysis of firm organization and management focuses on internal constraints to firm growth, theories of financial frictions emphasize external constraints such as the availability of credit to finance firm expansions.

One central indicator that differentiates theories of financial constraints and the life-cycle of firms is financial leverage. In limited commitment models of financial frictions, such as Buera (2009) and Moll (2014), leverage is constant across firms, so that the value of debt is constrained by the value of a firm's assets. These models would predict the absence of any particular systematic leverage dynamics as firms age and expand. In contrast, models of costly debt financing and default, such as Cooley and Quadrini (2001), predict that larger and more productive firms prefer to internally finance more of their operations to avoid costly credit. In this model, leverage systematically declines as firms grow and age. Since it is really firm profitability that drives the interaction of leverage and age, and profitability is proportional to size, Cooley and Quadrini (2001) can be considered to capture a size effect.

Another important friction that prevents young firms from acquiring credit on financial markets is private information about a firm's productivity and profit opportunities. Information about a firm's products and profitability might only diffuse to a wider public as it is active for a number of years. Diamond (1993) presents a model where banks, which specialize in acquiring information on firms, also optimally focus on providing short-term loans. On the other hand, for firms for which a large amount of public information is available, issuing long-term bonds is optimal. From this logic, one can see that as firms age and information about their business model becomes more public, older firms might switch their financing from obtaining short-term bank loans to issuing long-term bonds. This type of mechanism has no implications for overall leverage, but instead predicts that the debt maturity structure should lengthen as firms age. As learning by outside lenders takes time, this mechanism implies an age effect rather than a size effect.

2.3 Learning about Demand

Recent empirical work by Foster et al. (2013) suggests that firm age dynamics in homogeneous good industries cannot be driven by improvements in cost efficiency. Foster et al. (2013) instead suggest that firm age dynamics might be driven by active learning of firms about demand. In their model, firms can influence future demand by expanding demand today. This leads producers to dynamically set mark-ups, starting with low mark-ups to encourage more sales today which leads to demand accumulation tomorrow. As demand accumulation runs into diminishing returns, firms optimally increase their mark-ups eventually to maximize profits.

The key prediction for age dynamics is therefore that firms' mark-ups should systematically increase as firms become older. Furthermore, as Foster et al. (2013) show, one requires the past history of sales to credibly estimate this mechanism in contrast to pure size effects for which current firm size is mostly sufficient. We therefore classify the "learning about demand" channel as pure age effect.

2.4 Innovation

A classic form of knowledge accumulation as the result of purposeful investments are theories of endogenous innovation. Recent advances in this class of models generate a number of implications for firm life-cycle dynamics. Specifically, starting with work by Klette and Kortum (2004), endogenous innovation models generate realistic firm dynamics combining innovation by entrants with innovation by incumbents. The basic logic of models following in the tradition of Klette and Kortum (2004) is that firms are modeled as the sum of products for which a particular innovator has found the most productive technology. Firms expand by finding the new frontier technology in new product lines and shrink by losing product lines to other innovators. Through the lens of Klette and Kortum (2004), large firms are less likely to lose all product lines and exit and will therefore become older. At the same time, more products are not only a measure of firm size but also a measure of the knowledge accumulated at the firm, which makes future innovations more likely. Therefore, larger firms are more likely to innovate, since they accumulated more knowledge. In the model of Klette and Kortum (2004) if one would follow a cohort of firms as they age, older firms would be larger and more likely to innovate, but this is primarily a size effect.

Akcigit and Kerr (2010) offer an extension of the Klette and Kortum model in which young and small firms explore radical innovations while older and larger firms concentrate on non-radical innovations that focus on exploiting existing profit opportunities. In contrast to Klette and Kortum (2004), the model by Akcigit and Kerr makes predictions about the composition of the types of innovations generated by firms. As a result, the likelihood to generate radical innovations should decline with firm age and size, while the likelihood to generate non-radical, incremental innovations should increase. It should be noted that similar to the effects in Klette and Kortum (2004), these predictions are primarily driven by size effects. That is, the reason young firms tend to be more likely to pursue radical innovations is related to their size rather than the fact that they are not very old.

Innovations in Klette and Kortum (2004) and related models can be understood either as process innovations that imply a reduction in marginal production costs or as quality improvements of existing products. While these models are typically silent on the difference between product and process innovations, Klepper (1996) provides a theory of firm age dynamics that explicitly models this dimension. Young and small firms are more likely to generate product innovations, while old and large firms focus on process innovations. Klepper (1996) therefore provides additional predictions about the type of innovations likely to result as firms age. As in the case of endogenous innovation models discussed before, the theory of Klepper (1996) works primarily through firm size instead of age effects per se. The reason is that profits from process innovations scale with firm size, while profits from product innovations do not. This is the main reason older and larger firms specialize in process innovations, while smaller and younger firms specialize in product innovations.

3 Stylized Facts About Firm Age Dynamics

3.1 Data

The source of our data is the Workplace and Employee Survey (WES), which is a random stratified panel of establishments with the universe of Canadian firms as the target population and is conducted by Statistics Canada. The survey has a cross-sectional dimension of approximately 6500 firms per year over the time period from 1999 to 2006. Of these 6500 firms, we focus on the sample of around 5500 for-profit business firms. As in other government-sponsored surveys, response to the WES was mandatory, so that the overall response rate was typically close to 90%.

A particularly attractive feature of the WES survey implementation is that Statistics Canada invested considerable effort in ensuring the precise measurement of firm exit decisions. In typical establishment-level surveys, especially in the developing world, it is often unclear whether sample attrition is driven by firm exit or simply non-response. For the WES survey, Statistics Canada followed up non-respondents even up to a year later to find out whether the firm had indeed gone out of business. If not, every effort was made to convert non-respondents into respondents, which explains the very low attrition rate in the survey.

The WES provides various measures of firm organization and management practices as well as detailed measures of organizational change and innovation activity. Furthermore, in cooperation with Statistics Canada and with support of Industry

Canada, we linked the survey data to balance sheet information available from administrative tax records, the General Index of Financial Information (GIFI), which forms the basis for the calculation of profit taxes. We therefore create a comprehensive dataset not only of firms' management practices but also of their performance as reported to tax authorities.

Our combined dataset has several advantages compared to currently available empirical work on firm age dynamics, such as Foster et al. (2013) and Hsieh and Klenow (2014). First, our combined dataset is representative of the entire Canadian economy including the large service industry, rather than being limited to a few sectors such as manufacturing. Since the major part of economic activity in advanced economies such as Canada or the US takes place outside of manufacturing, we consider this a major advantage. Second, the scope of variables we are able to pool together from both the WES and firm balance sheet information surpasses anything available in current empirical studies, which are mostly based on sales and employment data, but typically cover neither internal firm organization nor balance sheet variables such as financial leverage or gross margins.

Finally, for measuring firm birth it might seem that our use of a representative survey is a disadvantage relative to Census-based studies such as Foster et al. (2013) and Hsieh and Klenow (2014). While by using Census data one can measure the birth year of firms as the first time a firm enters a Census, this strategy requires that the Census data have a very long time dimension. While the WES was conducted only for eight consecutive years, we can rely on birth year information that was directly asked in the survey and that we checked for consistency and validated with similar age information from the Canadian Annual Survey of Manufacturing.

3.2 Methodology

For our baseline empirical methodology, we follow Deaton (1997) to decompose age dynamics into cohort, time and age effects. In contrast to just analyzing cross-sectional size distributions by age, this approach has the advantage of separating age effects from cohort effects and possible aggregate shocks captured in time effects. We follow the literature in assuming that these three types of effects do not interact with each other, but take a (log) linear form:

$$\ln(y_{c,a,t}) = \mu + \sum_{a=1}^{A} \alpha_a \cdot D_a + \sum_{t=1}^{T} \tau_t \cdot D_t + \sum_{c=1}^{C} \kappa_c \cdot D_c + \texttt{controls} + \texttt{error} \tag{1}$$

where D_a, D_t, D_c are dummy variables for firm age, time period, and cohort, respectively. We define firm cohorts by their birth year and calculate each firm's age as the difference between the current year and the birth year. As is well known, the unrestricted linear model (1) is not identified, since each cohort dummy is by definition collinear to a combination of an age and a time dummy. We therefore impose four restrictions on the linear model to solve this collinearity problem and accommodate the constant term μ. We drop the first age and cohort effects to accommodate the constant μ, and we normalize time effects so that the time effects sum to zero in order to accommodate μ, $\sum_{t=1}^{T} \tau_t = 0$, and we require that those time effects are also orthogonal to a linear time trend, $\sum_{t=1}^{T} t \cdot \tau_t = 0$.

The logic of the Deaton methodology is that time effects can be interpreted as capturing business cycle movements, since they are orthogonal to any log linear time trend and sum to zero. A key advantage of the Deaton methodology is that the age dummies are flexible enough to pick up any form of non-monotonicities without imposing any particular functional form, while we are still able to plot the results.

The primary use of the Deaton methodology has typically been to construct synthetic panel data by tracking the same cohorts in different cross-sectional datasets over time. While one of the advantages of Deaton's method is the applicability to repeated cross sections, one might ask what specific advantages this method has in panel data. We would like to stress from the outset that for our object of interest – namely age effects – panel data does not necessarily address key identification issues such as the separation of age, cohort and time effects; see Hall, Mairesse and Turner (2007) and Schulhofer-Wohl (2013). Additionally, we argue that there are two particularly attractive features of the Deaton decomposition. First, since the age effects group together different establishments of the same age, it will naturally reduce attenuation due to two forms of noise prevalent in business micro-data: measurement error and temporary, mean-reverting shocks. As described in the data section, since age data is reported by survey respondents, it is prudent to safeguard against measurement error in this variable. Furthermore, it is well known since Baily, Hulten and Campbell (1992) that mean-reverting, temporary shocks are an important part of establishment dynamics. The Deaton method naturally reduces the impact of both forms of noise by calculating a mean for age effects across a number of establishments. Second, a key advantage of the availability of panel data is information about firm exit. This is particularly useful when considering age dynamics, since these age dynamics could often be driven by selection instead of, say, learning within establishments. Fortunately, the Deaton method allows us to exploit this feature of the panel data in a simple way by calculating age effects for non-exiting firms.

We also include a number of control variables in the vector `controls`. These are 4-digit NAICS sector fixed effects and dummies for multi-establishment firms as well as for exporter status. These controls help to make the estimated age patterns more representative for the entire economy.

3.3 Unconditional Firm Age Dynamics

We begin our empirical analysis by reporting results of age dynamics based on the Deaton decomposition discussed in section 3.2. This section serves several purposes. First, we quantitatively compare the age dynamics in our data with known cross-country empirical results from manufacturing reported by Hsieh and Klenow (2014). To facilitate comparability, we discuss the age effects on employment for the age classes 10 to 14 and 30 to 34 with the employment size for establishments with age 0 to 4, while showing the full set of age effects in the corresponding figures. Second, we document the same basic age dynamics for revenue as an alternative measure of establishment size and contrast the results of age dynamics in revenue with age dynamics in employment. Third, since results of the age dynamics in establishment employment and size are conditional on surviving firms, we explicitly analyze age patterns in exit dates.

Let us start by considering how well estimates of age effects in employment size based on the Deaton decomposition compare with age effects reported in Hsieh and Klenow (2014), which are constructed by following cohorts over time. Figure 2(a) shows our estimated age effects using the Deaton decomposition. They indicate that for the entire Canadian economy, the employment size advantage by age 10-14 is a factor of 1.56, while establishments by age 30-34 are on average 2.36 times larger than entrants, which are defined to be of age 0-4. The life-cycle patterns in the general economy are somewhat steeper for older establishments than the age dynamics of manufacturing plants. In manufacturing, establishments age 10-14 are 70% bigger than plants of age 0-4, while plants age 30-34 are 2.1 times bigger than entrants.[5] Putting these results into international perspective by comparing them with results from the US, Mexico and India—the main countries of the empirical study by Hsieh and Klenow (2014)—shows that Canada is between the extreme cases of the US and Indian manufacturing and has similar age dynamics to manufacturing in Mexico. Specifically, the age advantage of 10-to-14-year-old manufacturing plants in the US is 2.4, which is already larger than the Canadian manufacturing plants are at age 30-34, at which age US plants are 8 times bigger than the typical entrants of age 0-4. In contrast, Indian manufacturing plants barely grow, and even if they survive until the age of 30-34, are only around 40% bigger than the typical entrant. Mexican plants, on the other hand, behave similarly in their age dynamics to Canadian manufacturing plants. By age 10-14, the representative surviving Mexican plant is about 40% bigger than an entrant, compared to 70% in Canada. These are significant differences, but not as stark as between the US and Canada. What is more, this difference in age effects disappears by age 30-34, since both Mexican and Canadian manufacturing plants at this age are around 2.1 times bigger than a

[5] Manufacturing results are similar whether we use the Deaton decomposition or follow cohorts over time.

typical entrant.

Hsieh and Klenow (2014) also report age effects for an even broader set of countries, showing that most countries are somewhere between the extreme cases of India and the US in terms of their age dynamics. From this perspective, an analysis of the determinants of age dynamics in the Canadian economy could be considered quite representative of the mechanisms of such age dynamics in other countries. Furthermore, note that our age dynamics results for the entire Canadian economy are in the same ballpark as results for manufacturing. This might indicate that some of the same forces determining manufacturing age dynamics are at work in other sectors of the economy. This reinforces the value added of our analysis to the previous empirical literature that primarily focused on manufacturing due to data limitations.

A major part of the previous literature not only focused on manufacturing, but also used employment as the preferred measure of size. We will also consider revenue as an alternative measure of size since it has several attractive conceptual features. First, unlike inputs such as employment or capital, it is not likely to be subject to internal adjustment frictions, which make it possible that a firm's expectations of future profitability or uncertainty enter size measures. Second, revenue is a key outcome for theories of learning about demand such as Foster et al. (2013). Third, it provides an alternative measure of size dynamics with which we can check the robustness of the results using employment. Figure 2(b) displays the age dynamics for Canadian establishments, estimated using the Deaton methodology. As can already be seen when comparing figure 2(b) with figure 2(a), the age dynamics in revenue are much steeper than the age dynamics calculated using employment. An establishment of age 10-14 is approximately 2.6 times bigger in terms of revenue than an establishment of age 0-4. This revenue advantage becomes huge and is very slow to close. By age 30-35, surviving establishments are 11 times bigger than entering establishments. What is more, age effects in revenue show nearly no tendency to run into diminishing returns, in contrast to age effects in employment. Figure 2(a) shows that 35-year-old establishments are only marginally larger than 25-year-old establishments. In contrast, the same 35-year-old establishments are significantly larger in terms of revenue compared to 25-year-old establishments.

Our estimates of the age effects in employment and revenue focus on establishments that are surviving to minimize the impact of selection effects on the age dynamics. Yet, we know from previous studies that age has an important effect on firm exit decisions, especially of young firms. To prepare the analysis of correlation patterns of determinants of age dynamics with firm exit, we start by reporting in figure 3 exit patterns as a function of firm age. We used a linear probability model for these exit regressions. As the figure shows, there is a strong and significant decline in the probability of exit up to age 15-20. Past the age of 20, however, exit probabilities do not seem to be systematically related to establishment age. These patterns suggest that the determinants entering the age dynamics of employment and revenue are unlikely to be of similar importance for exit decisions.

4 Quantifying Sources of Firm Dynamics

In this section, we confront the different theories of firm life-cycle patterns outlined in section 2 with new stylized facts about age and size effects. Each subsection starts by describing a specific set of empirical measures related to the theories and then shows the age profiles of those measures. Throughout this section, age profiles reported are conditional on the sample of non-exiting firms, and we will analyze the effect of the various mechanisms on the extensive margin in the next section. Importantly, as emphasized in section 2, one should be careful to differentiate between size effects and pure age effects. Therefore, we also estimate the size effect of those measures conditional on controlling flexibly for age effects. Finally, we assess the success of those measures to explain the age profile of firm size. We do this by showing the "residual" age profile after partialling out on all measures jointly, and we also analyze the marginal explanatory power of each measure separately as well as all of them jointly. All in all, we believe that this new set of stylized facts will be informative for future theory development.

4.1 Firm Organization and Management Practices

Before we report the empirical results of firm organization and management practices, it should be emphasized that for our first three measures of firm organization, some interpolation is needed. The reason is that measures of decision layers, centralization and performance pay rely on data that is reported only every other year. To allow for maximum transparency, we choose to simply linearly interpolate data for the missing years. Data on the presence of professional management, outsourcing and organizational changes, on the other hand, are reported every year and require no adjustment.

4.1.1 Measurement and Age Profiles

Decision layers The WES includes detailed information regarding real decision authority on tasks across layers in the organizational hierarchy, which is the basis for our measures of decision layers and the degree of centralization.

In contrast to formal reporting patterns summarized in organizational charts, real decision authority avoids measurement issues that emerge if managers with formal authority merely "rubberstamp" decisions of subordinates; see Aghion and Tirole (1997). The survey questions are similar to measures of worker autonomy in Bresnahan, Brynjolfsson and Hitt (2002) and Bloom, Garicano, Sadun and Van Reenen

(2013b) in that they allow us to measure to what degree principals vs. agents are making decisions across 12 potential tasks. Specifically, the survey question is, "Who normally makes decisions with respect to the following activities?" The respondent is then given a choice of 12 possible activities, from "Daily planning of individual work" to "Quality control" to "Product and service development." There are six possible responses to the question of who makes decisions: non-managerial employees, work group, work supervisor, senior manager, individual/group outside the workplace—typically headquarters for multi-establishment firms—and business owners.

Our measure of decision layers counts the number of layers that are involved in any decision task among the 12 possible tasks in the survey. If a decision layer is not involved in any decision among those tasks, we infer that it is effectively not present. This strategy has both advantages and disadvantages when measuring organizational layers. One possible disadvantage is that our measure provides only a lower bound on the number of decision layers in the organizational hierarchy. Additional layers, which effectively do not play any role in decision-making even for very routine tasks such as "daily planning of work." could in principle exist in the organization and would be observed in organizational charts. At the same time, we also view this potential disadvantage as a unique advantage of our measure of layers. Specifically, it is likely that additional layers with no decision authority among any relevant tasks are simply a result of office politics and an inefficient growth of bureaucracy rather than an indicator of the division of labor within the organization. And while the growth of inefficient bureaucracy might be an interesting additional dimension to consider, we are much more interested in recent theories of knowledge hierarchies and the division of labor within organizations.

As outlined in the theory review section, the growth model of Garicano and Rossi-Hansberg (2012) would predict that young and innovative firms start out with few organizational layers and add more organizational layers as they commercialize and exploit their innovations. This would suggest that one observes an increase in the number of layers as firms age. But as figure 3(a) shows, no such pattern emerges from the data. The number of decision layers remains relatively constant up to age 30, at which point it significantly declines. One reason could be that our measure of organizational layers picks up de-layering at older establishments, which attempt to cut costs as they age to remain competitive. Yang, Kueng and Hong (2014) show that de-layering is more likely to happen at firms with low-cost business strategies, and Guadalupe and Wulf (2010) provide evidence of de-layering at US firms in response to trade shocks.

These results seem to stand in contrast to recent empirical work by Caliendo et al. (2014), who show that as firms grow in terms of value added, they increase the number of layers within the organization. It is here where a clear distinction between size and age effects is helpful. The focus of Caliendo et al. (2014) is not on the age dynamics, but on the correlation of the number of layers with firm size and wages. Indeed as we show below, within age classes, larger firms exhibit more organizational layers; see also Yang et al. (2014).

Centralization The measure of centralization is based on the same data of real decision authority described above, but it exploits more of the variation in tasks. Specifically, we separate decision layers into "managers" on the one hand, which include business owners, senior management and work supervisors, and "non-managerial employees" on the other hand. We focus on the difference between "managers" and "non-managers" for several reasons. First, data that allows us to differentiate between senior managers and business owners is only available for around half of the sample. Second, the model of Akcigit et al. (2014) seems to apply equally for the difference between managers and non-managerial employees, although it is stated in terms of business owners vs. managers.

Given this difference between managers and non-managerial employees, our measure of centralization counts the number of tasks that are exclusively completed by managers without any decision-making by non-managers. While our data in principle allows us to measure joint decision-making by managers and non-managerial employees, we instead focus on exclusive decision-making in order to make the results easier to interpret.

As was pointed out in the theory section, models of optimal delegation of real decision authority can have very different implications for firm age dynamics. Both Aghion and Tirole (1997) and Akcigit et al. (2014) focus on incomplete contracting as the key friction between managers and employees. But while decentralization of decision-making can be an optimal response as in Aghion and Tirole (1997), the optimal response in Akcigit et al. (2014) is stricter monitoring and centralization of decisions.

Figure 3(b) shows that neither of these predictions holds for the entire age dynamics. Indeed, it seems that up to age 27, firms tend to centralize more and more decision-making. This is possibly driven by the fact that professional managers and business owners are not differentiated in our measure of centralization. It is also compatible with the basic predictions of Akcigit et al. (2014). However, note that although not statistically significant, firms actually systematically reduce the degree of centralization past the age of 27. In this context, we would like to reemphasize that since theories of centralization are mostly driven by size effects instead of pure age effects, the evidence here needs to be considered in the light of the conditional size effects discussed below.

Performance pay The WES survey data offers a variety of information on performance-based compensation in firms. Specifically, it allows us to measure four different types of performance pay: individual incentive pay such as bonuses, commissions, piece-rates etc.; group or team incentives; profit sharing agreements; and stock-based compensation. Standard principal agent analysis characterizes very general forms of state contingent compensation contracts to solve the moral hazard problem. Consequently, we measure the presence of performance pay with an indicator that is one if any form of performance pay is present. We exclude stock compensation from this, since information on stock compensation is completely missing for one year and only a very small fraction of firms offer stock compensation to their employees. For more details on the performance pay data, see Hong, Kueng and Yang (2014a).

Figure 3(c) shows that although measured with considerable noise, the adoption probability declines as firms age. This supports the notion that young firms often specialize in innovative tasks, which involve considerable moral hazard, as emphasized by Holmstrom (1989).

Presence of professional management The WES also offers comprehensive information about the occupational composition of establishments. The survey reports the fraction of employees in each of seven possible occupational categories: managers, production workers, professionals, administrative staff, sales workers, technical support staff and "others." It also reports whether the employees hired in those categories are full or part-time employees. Since we are most interested in the presence of professional management hired by the business owner, we focus on the category of full-time managers.

Not surprisingly, the probability of firms hiring professional full-time managers strongly increases with age, as figure 3(d) shows. For very old firms, the likelihood of employing professional managers eventually bottoms out. This is driven by the fact that very few establishments that are older than 30 years do not employ any professional full-time managers.

Outsourcing To measure outsourcing, we utilize a part of the WES survey that asks establishments, "How many independent contractors provided products or services to your location?" The measure has the advantage that it focuses not only on intermediate inputs but also on labor services that are hired outside the firm. We would like to emphasize at this point that our measure of outsourcing should not be understood as a comprehensive indicator of outsourcing. It is likely to capture issues regarding firm boundaries only very roughly. For instance, it might still be possible that although outside contractors are legally independent, they are closely connected and permanently dependent on the purchasing firm, as in the famous "GM-Fisher Body" example. We will not be able to capture those types of "vertically integrated but in legal terms only" examples.

Figure 3(e) shows that as expected from the theory review in section 2, the likelihood of outsourcing strongly and monotonically increases with firm age. This pattern can be seen as indicative that firm boundary patterns might be strongly affected by firm life-cycles. However, in the absence of any information about the nature of tasks that are outsourced, there are also alternative explanations, such as the reduced hold up explanation offered earlier. For instance, firms might expand their intermediate input varieties over time, making it more likely that at least one of the varieties needs to be supplied by an outside contractor.

Organizational changes All of the measures presented in this section are capturing the current status of internal firm organization and management practices. A complementary perspective to the question of whether an organization adopted a certain practice is the question of whether organizations change practices more often as they age. Literature on this phenomenon of organizational adaption and learning has been scarce in economics, mainly due to the lack of reliable data. This is in contrast to related fields, such as management science, which has developed extensive theories of "organizational learning"; see for instance Levitt and March (1988).

We include a brief analysis of patterns of organizational change over the firm life-cycle. Our analysis here should be taken as very preliminary, especially in the absence of any solid economic theory. We base our analysis on a section of the WES survey that asks establishments, "Has your workplace experienced any of the following forms of organizational change during the last year?" Examples of these changes include "Greater integration among functional areas," "Downsizing," "Re-engineering," "Implementation of TQM," and many more, including a residual category of "other changes." As is clear from these examples, these organizational changes focus mainly on changes in the formal organizational structure of an establishment. The data is therefore unable to actually speak to the organizational learning literature exemplified by Levitt and March (1988), since this literature focuses mainly on hard-to-measure "organizational routines."

To obtain a single measure of overall organizational change and to reduce the noise in the data, we sum across all 15 categories of organizational change categories. Figure 3(f) displays the results from using the Deaton decomposition to measure the age dynamics of organizational change. As firms get older, the extent of organizational change slows down considerably. This slowdown in the degree of organizational changes might reflect diminishing returns to learning as establishments age. It is compatible with possible vintage effects in organization capital emphasized by Atkeson and Kehoe (2005). Since the overall measures of organizational change are hard to match to the management practices we discussed in previous sections, we abstain from further utilizing this evidence in the analysis that follows.

4.1.2 Conditional Size Effects

Column 2 in tables 1 and 2 reports results from including proxies for management practices in the Deaton decomposition. Table 1 uses log employment as the dependent variable, while 2 uses log revenue. Remember that model (1) estimates age effects non-parametrically under the restrictions of the Deaton decomposition. The coefficient on the theory proxy variables are therefore correlations of these proxies with size, controlling for age effects as well as indicators for multi-establishment firms and exporters, a full set of 4-digit NAICS sector fixed effects, and Deaton time and cohort effects.

The results show that for both the presence of management and for outsourcing, the size effects are similar to the age effects estimated earlier. Larger firms of a given age are more likely to hire professional managers and outsource activities, in much the same way as older firms are more likely to pursue these practices. Note that for both sets of mechanisms, we pointed out possible size effects as well as learning mechanisms which imply pure age effects. The existence of systematic size effects, even after controlling for age, suggests that for outsourcing and adoption of professionalized management, size effects and learning effects both matter.

For the other management practices, however, different patterns emerge, indicating that one cannot simply equate age effects with size effects. Importantly, and in contrast to the age dynamics, the conditional size effects are more in line with the predictions derived from standard theories summarized in section 2. This can be most clearly seen for our measure of decision layers. Remember that the estimated age dynamics indicated that the number of layers seems to decline over the life-cycle, especially for very old establishments. But old establishments, as we showed in section 3, are also larger establishments. Hence these age dynamics seem to stand in contrast to empirical work by Caliendo et al. (2014) who, using an alternative proxy for number of organizational layers, show that larger firms exhibit more layers. Column 2 in tables 1 and 2 shows that this pattern also holds in our data. Controlling for age, larger firms have more decision layers, whether size is measured by total employment or by revenue.

Similarly, the age effects showed older firms are not more likely to be decentralized, contrary to the intuition that larger firms should decentralize more tasks. However, controlling for age as in tables 1 and 2, we do find that larger firms systematically centralize less tasks. Note that these correlations still stand in contrast to predictions from models such as Akcigit et al. (2014), in which larger firms should be more centralized.

In this context, we argued in section 2 that larger firms might be subject to more prevalent moral hazard problems, since it is harder for principals to monitor many employees. This prediction is borne out in the correlation of establishment size and the adoption of performance pay. Large firms are indeed more likely to adopt performance pay, even though the unconditional probability of adopting performance pay declines weakly in age.

4.2 Financial Frictions

We now turn to theories of financial frictions as explanations for the age dynamics of firms. As outlined in section 2, financial leverage is a simple, yet meaningful statistic to differentiate theories of the effects of financial frictions on firm dynamics.

4.2.1 Measurement and Age Profiles

We obtain leverage data from balance sheet information that Canadian tax authorities collect in the context of calculating profit tax liabilities. We link the administrative tax records, assembled in the previously mentioned GIFI, with the WES via the Canadian business register. Leverage is measured as the log of the ratio of a firm's overall assets to the implicit equity, defined as the difference between total assets and total debt liabilities. This measure approximates the debt-equity ratio well for low levels of debt (which is typical for the businesses in our sample) and is less subject to large outliers than the direct measure of debt to equity. Remember that theories of costly debt financing and default, such as Cooley and Quadrini (2001), predict systematically decreasing leverage in size (but not necessarily in age), theories of limited commitment frictions such as Moll (2014) predict constant leverage.

Figure 4(a) demonstrates that there is no systematic trend in financial leverage over the firm life-cycle. To be sure, the data is quite noisy, but note that the point estimates of the age effects are virtually flat until age 25. This stands in contrast to the predictions for leverage from models of firm dynamics explaining age effects using costly debt financing, such as Cooley and Quadrini (2001). On the other hand, the empirical patterns seem broadly compatible with theories of limited commitment frictions, as leverage is predicted not to exhibit any age effects. It should be emphasized that since the main mechanism in Cooley and Quadrini (2001) depends on profitability and therefore size, the age predictions per se are not sufficient to cast doubt on the theory.

A second dimension of financial frictions is the maturity structure of debt. Here we utilize the same GIFI balance sheet data as before to calculate the log of the ratio between short-term and long-term debt. As can be seen in figure 4(b), this ratio slowly rises over time, as older firms seem to be able to substitute more long-term debt for costly short-term debt. The effects are too noisy to pick up systematic patterns with any degree of confidence, though. Models of financial frictions relying on debt maturity structure channels might therefore only be of limited importance.

4.2.2 Conditional Size Effects

One result of the previous analysis is that the age dynamics of leverage seem to contradict popular models of financial frictions such as Cooley and Quadrini (2001). At the same time, the shift from costly debt to internal financing at the heart of Cooley and Quadrini (2001) seems to be a size effect rather than a pure age effect. Column 3 in tables 1 and 2, therefore, show the results of including financial leverage in the Deaton decomposition. One would therefore expect that larger and more profitable firms have lower levels of leverage. As can be seen, the correlation of establishment size and leverage conditional on age is positive, contrary to what theory predicts. Hence, not only are the age dynamics of leverage incompatible with the costly debt financing effect in Cooley and Quadrini (2001), but size correlations with leverage conditional on age also do not offer much support.

The age dynamics of leverage were much more supportive of models of limited commitment financial frictions such as Buera (2009) and Moll (2014). The natural question therefore is whether size-leverage correlations are as supportive. Unfortunately, the answer is no, since baseline limited commitment financial frictions models would predict that leverage is a constant that is independent of firm size.

4.3 Learning about Demand

To quantify the importance of active learning about demand, as emphasized in the structural model of Foster et al. (2013), we measure the dynamics of mark-ups predicted by their theory for the entire sample of firms across all industries, instead of focusing on manufacturing only.

4.3.1 Measurement and Age Profiles

We pursue two alternative measures of mark-ups. Our first measure is taken directly from the accounting data in GIFI and captures gross margins of sales. It is defined as the log difference between operating revenue and costs of goods and services sold (or COGS). To the degree that COGS captures the variable costs used for production of goods and services, gross margins should be a good proxy for mark-ups. They also have the unique advantage of being exclusively data-driven instead of relying on any type of timing or structural identification assumption. However, around a third of the firms in our sample do not provide information on COGS, so it seems prudent to pursue alternative measures of mark-ups.

As a primary alternative, we use GMM-based mark-up measures proposed by Ackerberg, Caves and Frazer (2006). This estimator relies on a set of timing assumptions, including the assumption that intermediate goods like electricity and materials are acquired in frictionless spot markets, while other inputs such as capital are predetermined one period in advance. The advantage of this GMM procedure is that it allows us to construct measures for mark-ups for nearly all establishments in our sample. The main caveat is that it relies on cost minimization and timing assumptions to be valid.

Figures 5(a) and 5(b) report the results from applying the Deaton decomposition to the two alternative measures of mark-ups. While both measures show a qualitatively similar pattern of rising mark-ups over the firm's life-cycle as predicted by the structural model of Foster et al. (2013), the noise—especially in the gross margin—complicates statistical inference. The structural mark-up measure, on the other hand, shows both a statistically and an economically significant increase in mark-ups over the life-cycle. However, the fact that it takes over 20 years for those effects to show up in the data is somewhat surprising. The GMM-based measure will serve as our primary proxy for mark-ups in the rest of the analysis, since it is available for a broader sample of firms.

4.3.2 Conditional Size Effects

The fourth column in table 1 and 2 reports conditional size effects of markups. The results differ, depending on whether employment or revenue is taken as the measure of size. While the correlation of mark-ups and employment is negative, the correlation of mark-ups and revenue is systematically positive. One possible explanation for this puzzling pattern could be that the mark-up measures based on Ackerberg et al. (2006) reflect revenue productivity of labor to a large degree and that the correlations we find, once we control for age effects, are to a large degree mechanical.

4.4 Innovation

4.4.1 Measurement and Age Profiles

We rely on survey measures of innovative activity which are included in the WES dataset as our baseline data for theories of endogenous innovation. The WES asks respondents to report four possible types of innovations: new products or services, new processes, improved products or services, and improved processes. The survey form asks establishments to categorize innovations that "differ significantly in character" from products or processes used before as new. In this sense, the difference between "new" and "improved" could be interpreted to capture the difference between drastic and incremental innovations. We validate these innovation measures in Hong, Kueng and Yang (2014b), by showing that the measures of innovation are significantly correlated with firm growth and that innovation by other firms in the industry significantly depresses growth at non-innovating firms. These results are consistent with findings for similar innovation surveys for other countries; see Mairesse and Mohnen (2010).

Starting with process innovations, remember that older firms in a baseline model of Klette and Kortum (2004) are more likely to innovate, since they consist of more products and therefore benefit from stronger knowledge spillovers. Using indicators for process innovations, figures 6(a) and 6(b) show that exactly the opposite pattern holds in the data. Smaller and younger firms are more likely to generate process innovations than are older firms. To the degree that "new process innovations" displayed in figure 6(a) can be understood as "radical innovations," this pattern is compatible with extended Klette-Kortum models such as Akcigit and Kerr (2010), in which younger firms pursue radical explorative innovations, while older firms specialize in incremental exploitative innovations. Note, however, that this evidence is only a qualified success for the model of Akcigit and Kerr (2010), for two reasons. First, it seems that in their own empirical work they consider process innovations as being close to incremental innovations. If this were the correct mapping, then one would expect that older firms would be more likely to innovate in process innovations, just as in the baseline Klette-Kortum model. Second, note that even if new process innovations could be mapped to Akcigit and Kerr's radical innovations, one would still expect that the baseline predictions from the Klette-Kortum model would continue to apply to improved process innovations shown in figure 6(b). However, this graph displays a probability of incremental process innovations that is declining with firm age as well, albeit with a less negative slope.

An alternative interpretation of the Klette-Kortum model would map the innovations in this model into product innovations. This might be the correct mapping, if by product innovations respondents refer to product innovations that are new to the firm instead of new to the economy. Unfortunately, even this broad interpretation of the Klette-Kortum model and its extension by Akcigit and Kerr (2010) does not generate the correct life-cycle dynamics of innovation, as figures 6(c) and 6(d) show. In fact, the patterns of innovation for new or improved products are even at odds with models of innovation explicitly constructed to explain the difference between product and process innovations, such as Klepper (1996). As previously discussed, this model would predict that the probability of product innovations declines in firm age, while the probability of process innovations increases in firm age. In contrast, the data displays no significant relation between product innovation and age, while the probability of process innovations sharply declines in firm age.

Theories of incumbent innovation such as Klette and Kortum (2004) clearly exhibit difficulties to match the age dynamics of innovation in our data. We draw two main conclusion from the analysis of the data. First, as emphasized in section 2, the Klette-Kortum and related models operate through size effects, so it is worthwhile to consider evidence on innovative activity of large vs. small firms to look for support of this class of theories. Second, there is clearly more need for detailed data development on the difference between product and process innovations. However, to the extent that the results gathered in this section are indicative, models of product and process innovations, such as Klepper (1996), have difficulties matching the joint age dynamics of these types of innovations. Further theory development on the joint dynamics of product and process innovation is clearly needed.

4.4.2 Conditional Size Effects

Current models of incumbent innovation such as Klette and Kortum (2004) have a hard time matching innovation patterns over the life-cycle in our data. However, as emphasized during the theory review of section 2, Klette and Kortum (2004) and related models such as Akcigit and Kerr (2010) should be understood as models making predictions about firm size and innovation rather than firm age and innovation.

Furthermore, to differentiate theories of endogenous innovation from technology adoption and imitation, we exploit additional information on technology adoption from the WES. The WES survey asks respondents to report spending on three different categories of new technology: computers/software, CAD/CAM technology and remaining "other technologies." We sum up the spending on all three types of new technology and normalize it by establishment revenue to arrive at measures for technology intensity.

Results, including technology adoption and innovation variables in the Deaton decomposition, are reported in column 5 of tables 1 and 2. For the innovation variables, these results are very much compatible with predictions from incumbent innovation models such as Klette and Kortum (2004). Controlling for age effects, larger establishments tend to be more likely to innovate. Note, however, that results are strongest for improved processes and to a lesser extent for improved products and services, while the results for new innovations depend on the measure of firm size. To the degree that the difference between "new" and "improved" products or processes can be considered to capture the differences between radical and incremental innovations, the patterns shown in tables 1 and 2 stand somewhat in contrast to predictions by Akcigit and Kerr (2010). The model of Akcigit and Kerr (2010) would predict that smaller firms are more likely to innovate in "new" technologies, so that the correlation with establishment size should be negative.

4.5 Residual Age Dynamics

How does controlling for different theoretical mechanisms of firm age dynamics affect the estimated age effects from the Deaton decomposition? To answer this question, we return to the sample statistics we computed in section 3, where we compared the Canadian data to other international benchmarks from Hsieh and Klenow (2014). As before, we focus on the age effects by ages 10-14 as well as 30-34. Table 4 displays the age effects, controlling for different proxies of firm age dynamics. As before, we group age dynamics theories together in the four categories firm organizational capital and management practices, financial frictions, dynamic mark-ups, and innovation, each corresponding to a different row in the table. The first row "none" repeats age effects for employment or revenue without any proxy variables for firm age dynamics theories. As we follow the age effects down the rows of table 4, we track the impact of including different proxy variables on the age effects. The more successful these variables are in capturing firm age dynamics, the closer to one should be the residual age effects reported in this table.

Starting with total employment as dependent variable in the Deaton decomposition, the first two columns of table 4 reveal two main stylized facts. First, including organizational capital and management practices reduces residual age effects by the largest amount. This becomes especially clear when comparing the effects of organizational capital and management practices on innovation. Including variables of innovation actually increases residual age effects instead of lowering them. Second, overall the four types of theories for age dynamics do reduce age effects by around 25%. On the one hand, this can be considered a significant reduction in the residual age dynamics. On the other hand, a majority of firm age dynamics still remains unexplained, despite the fact that our proxy variables capture a variety of prominent firm life-cycle theories. One of the main reasons for this result seems to be that some factors such as innovation actually increase residual age effects. Furthermore, as we document in figure 7(a), although there is a significant reduction in firm age effects around age 20, this effect disappears as plants age further.

However, results on total employment stand in contrast to revenue results as reported in the last two columns of table 4. As before, organizational capital and management practices substantially reduce age effects on revenue. On the other hand, learning about demand as captured in dynamic mark-ups also tends to reduce age effects in revenue considerably. This strong effect of learning about demand on revenue is intuitive, since revenue is much more closely related to demand than total employment. As a result, by age 34, age effects on revenue are only 60% of their level before controlling for theories of firm age dynamics. This is despite the fact that measures of innovation, as before, actually tend to increase these age effects, as shown in the 5th column of table 4. Figure 7(b) shows another difference of conditional age dynamics in revenue and total employment. While the age effect of controlling for firm age dynamics theories eventually dissipates when using total employment, those age effects become stronger when using revenue as a measure of firm size.

4.6 Explanatory Power of the Theories

We now move to the question of how much of the life-cycle patterns can be explained by the different firm age dynamics theories. Our principal metric to compare the contribution of the various theories is the change in adjusted R^2 in the Deaton decomposition if proxies for those theories are included as additional explanatory variables. We group the specific theories into the four broad categories used before: firm organization and management practices, financial frictions, learning about demand, and innovation. We focus much of our emphasis on comparing the age dynamics in employment and the life-cycle of revenue, since these are alternative measures of establishment size. As before, all results regarding age dynamics are conditioned on the set of non-exiting firms during the sample period. A discussion of the life-cycle pattern of exits follows in the next section.

The last line in tables 1 and 2 reports adjusted R^2 values from including the proxy variables, first individually and finally jointly. For comparison purposes, the first column of both tables reports the Deaton decomposition without any proxy variables added. At least three noteworthy patterns emerge. First, measures of firm organization and management practices are the most important factors in improving the explanatory power of the Deaton decomposition. The adjusted R^2 with total employment as a measure of size increases from 0.316 to 0.481, while in the revenue regression it increases from 0.375 to 0.5. No other set of theories is as successful in capturing the variation in size across firms, controlling for firm age. In particular, note that although including all variables jointly in column 6 helps improve the fit, the majority of the increase in explanatory power is attributable to firm organization and management practices. Second, proxies for endogenous growth models are the second most important set of variables. Despite this fact, the innovation variables are not nearly as successful in explaining size variation. Third, note that for most of the organizational capital and management practice variables, point estimates remain stable even when including all other variables. This stands in contrast to innovation variables, which sometimes change substantially in magnitude.

5 Exit Patterns

In the Deaton decompositions of firm size in the previous section, we controlled for selection effects along the firm life-cycle by focusing on the set of surviving firms. To consider selection effects, we analyze a Deaton decomposition with firm exit as dependent variable in table 3. It turns out that the most important set of explanatory variables is not organizational capital or management practices, learning about demand, or innovation. Instead, financial variables such as leverage and especially debt maturity structure have significant explanatory power for firm exit, once age effects are controlled for. That is, controlling for firm age, firms with higher leverage and more long-term debt are less likely to exit. These stylized facts suggest that financial variables might influence firm dynamics primarily through selection instead of by impacting firm growth.

However, it should be noted that, as before, most of the variation in exit remains unexplained, as the last row in table 3 shows. Similarly, age effects from the Deaton decomposition shown in figure 7(c) are virtually unaffected by including the various proxy variables for firm life-cycle models.

6 Conclusion

This paper is a first step in exploring the empirical importance of several theories of firm age dynamics. Models proposing specific mechanisms that drive firm growth over the life-cycle are a crucial complement to studies about the sources of firm performance differences. Throughout our empirical analysis, our focus is not only on stylized facts that are consistent with current theory, but also on novel empirical insights that provide opportunities for further research. Here, the difference between age dynamics generated through size effects and age dynamics that are independent of size effects seems crucial. While many current theories successfully describe size effects, there is a clear shortfall of models that generate age dynamics independent of size.

The stylized facts presented in this paper can be considered a starting point for theory development in several areas relating to firm dynamics. First, in the area of organizational capital accumulation and management practices, learning models with implications for optimal firm organization and management practice adoption seem promising. Not only is survey evidence by Bloom et al. (2013a) consistent with a theory of learning, but age profiles of all organizational capital variables and management practices we analyze exhibit strong life-cycle effects, which cannot be explained by size effects alone.

Second, endogenous growth models of firm dynamics and incumbent innovation need to be extended to match the age profiles of innovation activity. Beyond the fact that age profiles tend to be downward sloping, in contradiction to current theory, there seem to be systematic differences in product and process innovations when analyzing size effects. These differences are currently not captured by prevailing models of innovation.

Third, models of financial frictions currently focus on intensive margin firm growth implications. While relatively uninformative for intensive margin firm growth patterns, we find that a firm's capital structure plays an important role in predicting firm exit, conditional on firm age. These results suggests that theories of financial frictions focusing on extensive margin effects are a natural way forward for models of credit constraints. Such models would also put extensive margin misallocation at the center of the welfare analysis of financial crises and credit crunches.

Overall, the novel avenues for theory development that our stylized facts open are likely to have major implications for the welfare analysis of firm dynamics and for policies that affect innovation, international competitiveness, and firm growth in the long run.

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Table 1: Size effects conditional on age using log employment

Dependent: log empl.	(1)	(2)	(3)	(4)	(5)	(6)
Organization and Mgmt						
has a mgmt layer		0.513***				0.496***
		(0.047)				(0.046)
does outsourcing		0.155***				0.151***
		(0.031)				(0.033)
uses performance pay		0.269***				0.251***
		(0.031)				(0.031)
# of decision layers		0.245***				0.236***
		(0.017)				(0.016)
# of centralized tasks		-0.016***				-0.016***
		(0.005)				(0.004)
Capital Structure						
log asset/equity			0.069***			0.027**
			(0.015)			(0.011)
log short/long debt			-0.057			-0.047
			(0.092)			(0.083)
Dynamic Mark-Ups						
log mark-up				-0.090***		-0.062***
				(0.025)		(0.022)
Innovation						
new process innovation					0.082**	0.037
					(0.039)	(0.032)
new product innovation					0.033	-0.040
					(0.037)	(0.037)
improved processes					0.232***	0.120***
					(0.052)	(0.035)
improved products					0.081**	0.047
					(0.037)	(0.032)
technology intensity					-0.331	-0.712
					(0.545)	(0.470)
Age FEs	YES	YES	YES	YES	YES	YES
Deaton time FEs	YES	YES	YES	YES	YES	YES
Cohort FEs	YES	YES	YES	YES	YES	YES
Sector FEs	YES	YES	YES	YES	YES	YES
Additional controls	YES	YES	YES	YES	YES	YES
Obs.	23,241	23,241	23,241	23,241	23,241	23,241
R^2	0.330	0.492	0.334	0.333	0.352	0.498
Adj R^2	0.316	0.481	0.320	0.319	0.338	0.487

Notes: Sector fixed effects are 4-digit NAICS industries. "Other controls" are multi-establishment exporter status indicators. Regressions use sample weights. Heteroskedasticity- and autocorrelation-consistent (HAC) standard errors are in parentheses, clustered by sampling strata, which are broad industry-size-region categories. ***, **, * indicates significance at or above 1%, 5%, or 10%, respectively.

Table 2: Size effects conditional on age using log revenue

Dependent: log revenue	(1)	(2)	(3)	(4)	(5)	(6)
Organization and Mgmt						
has a mgmt layer		0.630***				0.698***
		(0.063)				(0.062)
does outsourcing		0.279***				0.213***
		(0.043)				(0.039)
uses performance pay		0.371***				0.377***
		(0.044)				(0.040)
# of decision layers		0.303***				0.299***
		(0.017)				(0.022)
# of centralized tasks		-0.024***				-0.024***
		(0.007)				(0.006)
Capital Structure						
log asset/equity			0.157***			0.066***
			(0.020)			(0.015)
log short/long debt			0.152			0.190**
			(0.122)			(0.094)
Dynamic Mark-Ups						
log mark-up				0.610***		0.647***
				(0.033)		(0.028)
Innovation						
new process innovation					-0.021	-0.023
					(0.062)	(0.052)
new product innovation					0.092**	-0.055
					(0.042)	(0.044)
improved processes					0.405***	0.186***
					(0.053)	(0.050)
improved products					0.040	0.009
					(0.046)	(0.043)
technology intensity					-2.401***	-1.849***
					(0.793)	(0.588)
Age FEs	YES	YES	YES	YES	YES	YES
Deaton time FEs	YES	YES	YES	YES	YES	YES
Cohort FEs	YES	YES	YES	YES	YES	YES
Sector FEs	YES	YES	YES	YES	YES	YES
Additional controls	YES	YES	YES	YES	YES	YES
Obs.	23,241	23,241	23,241	23,241	23,241	23,241
R^2	0.388	0.514	0.398	0.462	0.405	0.603
Adj R^2	0.375	0.504	0.385	0.450	0.392	0.595

Notes: Sector fixed effects are 4-digit NAICS industries. "Other controls" are multi-establishment exporter status indicators. Regressions use sample weights. Heteroskedasticity- and autocorrelation-consistent (HAC) standard errors are in parentheses, clustered by sampling strata, which are broad industry-size-region categories. ***, **, * indicates significance at or above 1%, 5%, or 10%, respectively.

Table 3: Effects on exit probability

Dependent: I(exit)	(1)	(2)	(3)	(4)	(5)	(6)
Organization and Mgmt						
has a mgmt layer		-0.000				0.002
		(0.007)				(0.007)
does outsourcing		-0.005				-0.004
		(0.004)				(0.004)
uses performance pay		-0.008*				-0.007*
		(0.004)				(0.003)
# of decision layers		0.001				0.001
		(0.002)				(0.002)
# of centralized tasks		-0.001**				-0.001**
		(0.001)				(0.001)
Capital Structure						
log asset/equity			-0.009**			-0.008**
			(0.004)			(0.004)
log short/long debt			-0.039**			-0.036**
			(0.017)			(0.016)
Dynamic Mark-Ups						
log mark-up				0.003		0.003
				(0.004)		(0.004)
Innovation						
new process innovation					0.008**	0.008*
					(0.004)	(0.005)
new product innovation					-0.006	-0.003
					(0.005)	(0.006)
improved processes					-0.001	0.001
					(0.003)	(0.003)
improved products					-0.005	-0.005
					(0.005)	(0.005)
technology intensity					-0.135***	-1.23**
					(0.049)	(0.052)
Age FEs	YES	YES	YES	YES	YES	YES
Deaton time FEs	YES	YES	YES	YES	YES	YES
Cohort FEs	YES	YES	YES	YES	YES	YES
Sector FEs	YES	YES	YES	YES	YES	YES
Additional controls	YES	YES	YES	YES	YES	YES
Obs.	24,936	24,936	24,936	24,936	24,936	24,936
R^2	0.109	0.112	0.116	0.109	0.110	0.119
Adj R^2	0.091	0.094	0.098	0.092	0.092	0.101

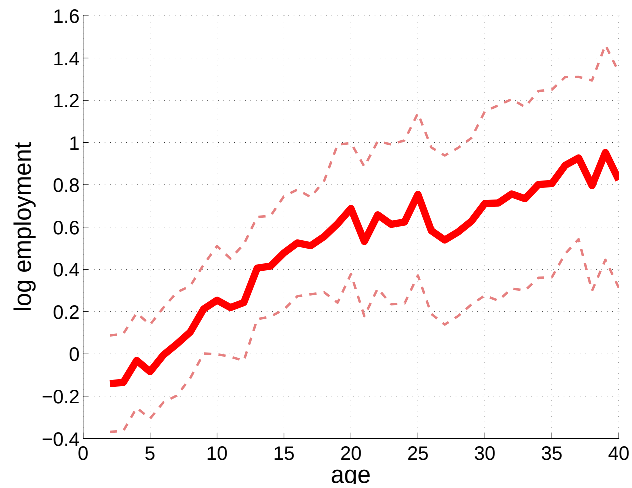
Notes: Sector fixed effects are 4-digit NAICS industries. "Other controls" are multi-establishment exporter status indicators. Regressions use sample weights. Heteroskedasticity- and autocorrelation-consistent (HAC) standard errors are in parentheses, clustered by sampling strata, which are broad industry-size-region categories. ***, **, * indicates significance at or above 1%, 5%, or 10%, respectively.

Table 4: Contributions to firm size relative to age bin 0-4

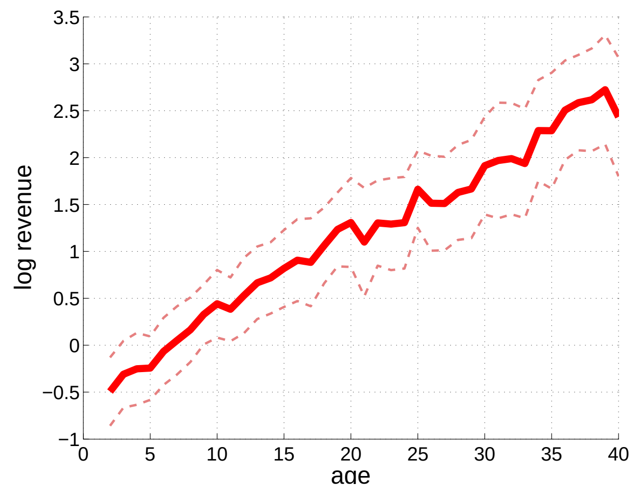
Dependent variable	employment		revenue	
Age bin	10-14	30-34	10-14	30-34
Additional determinants				
None	1.57	2.36	2.58	11.23
Organization and Mgmt	1.42	2.03	2.24	8.75
Capital Structure	1.56	2.39	2.56	11.56
Dynamic Mark-Ups	1.56	2.47	2.64	8.38
Innovation	1.62	2.69	2.61	12.53
All	1.43	2.19	2.30	6.72

Notes: The table shows the average firm size for age bins 10-14 and 30-34 relative to age bin 0-4, after controlling for various mechanisms suggested by theoretical models. The regressions also partial out sector, cohort, and Deaton time fixed effects as well as multi-establishment and exporter status; they use sample weights.

Figure 1: Unconditional life-cycle profile of size and exit



(a)



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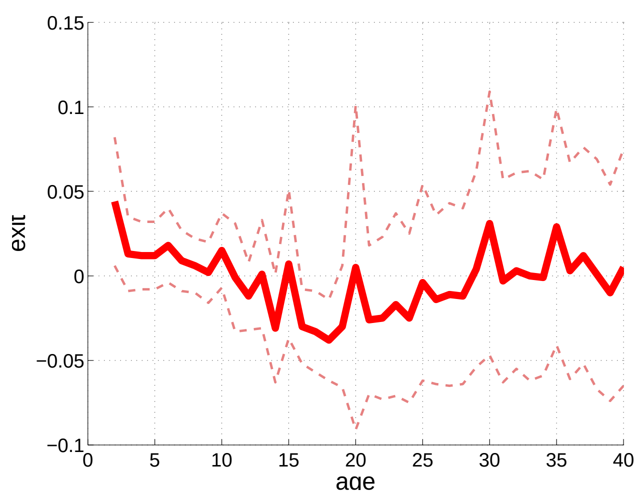
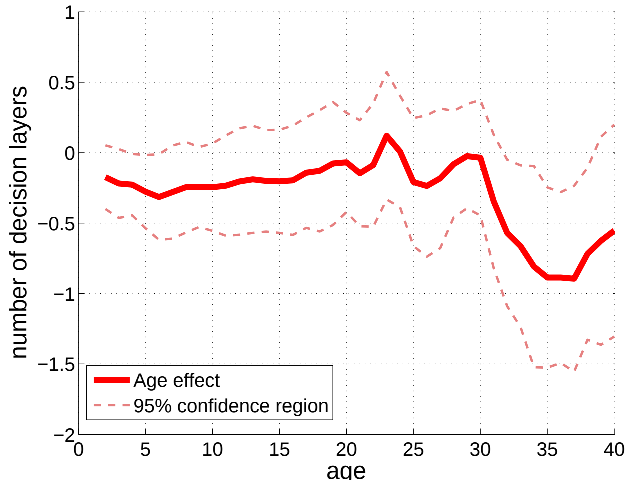


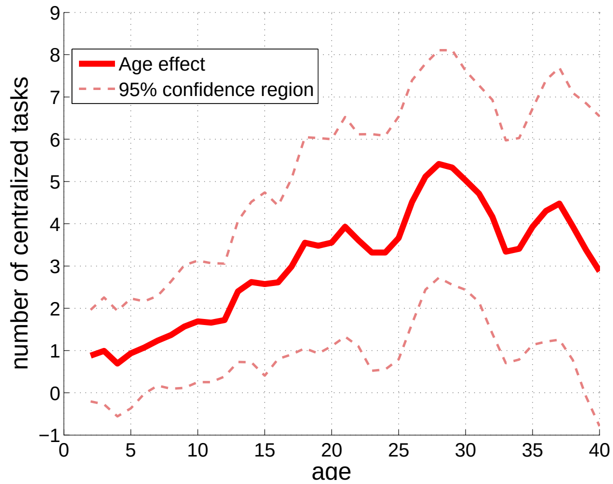
(c)

Notes: Age effects are estimated using the Deaton (1997) decomposition. See the text for more details.

Figure 2: Unconditional life-cycle profile of organizational capital and management practices



(a)



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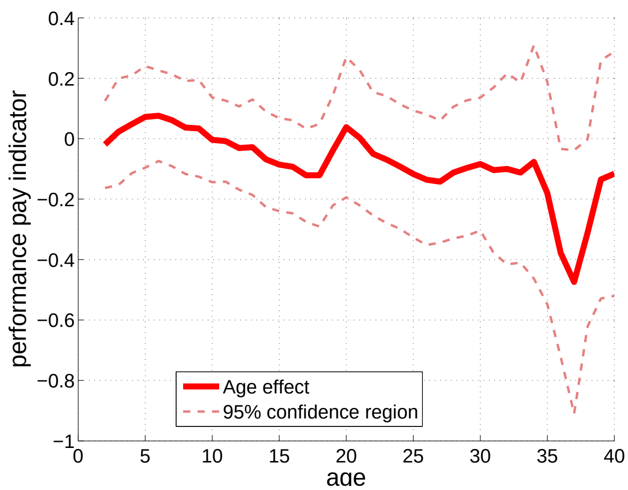

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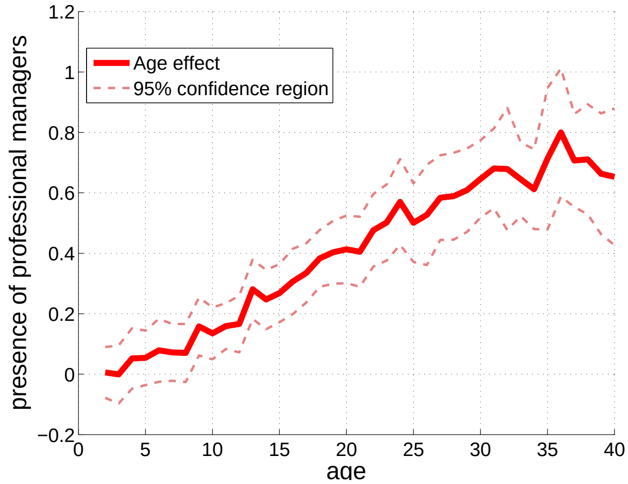
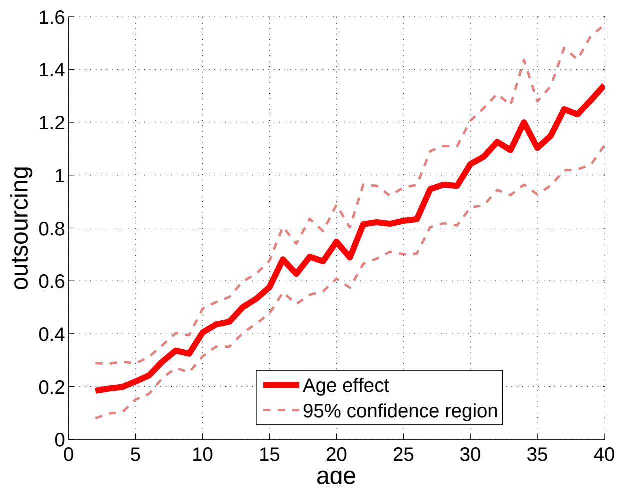
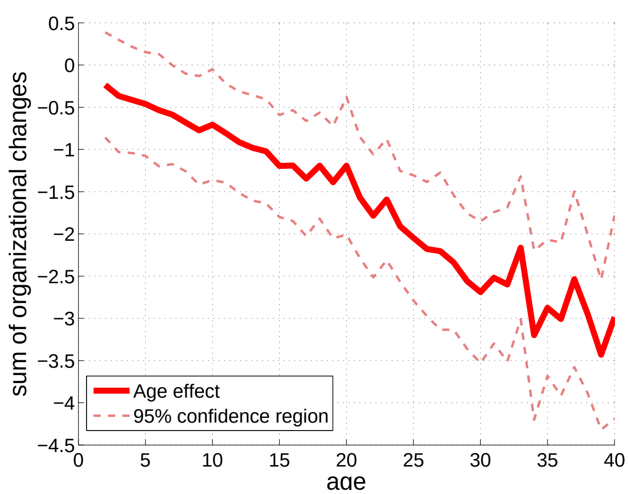
Figure 2: Unconditional life-cycle profile of organizational capital and management practices (cont.)



(d)



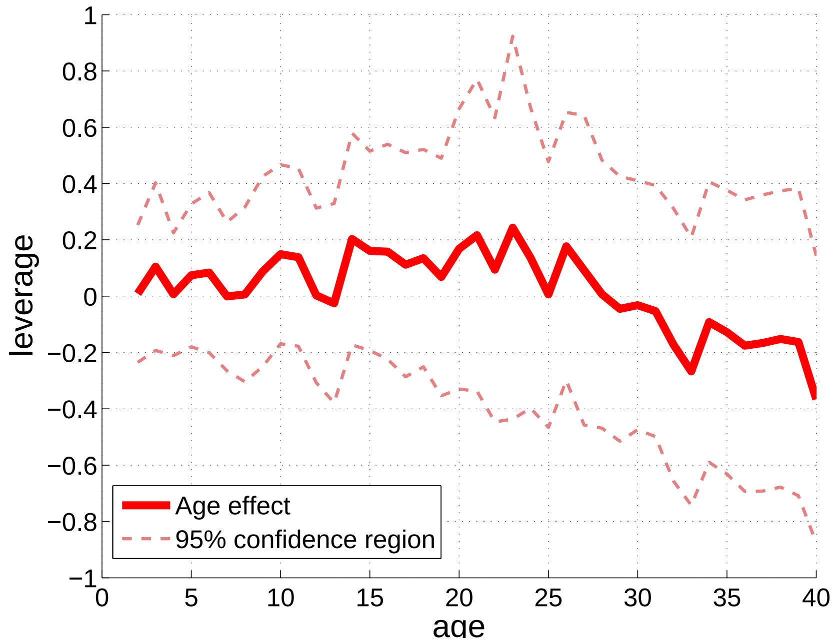
(e)



(f)

Notes: Age effects are estimated using the Deaton (1997) decomposition. See the text for more details.

Figure 3: Unconditional life-cycle profile of capital structure



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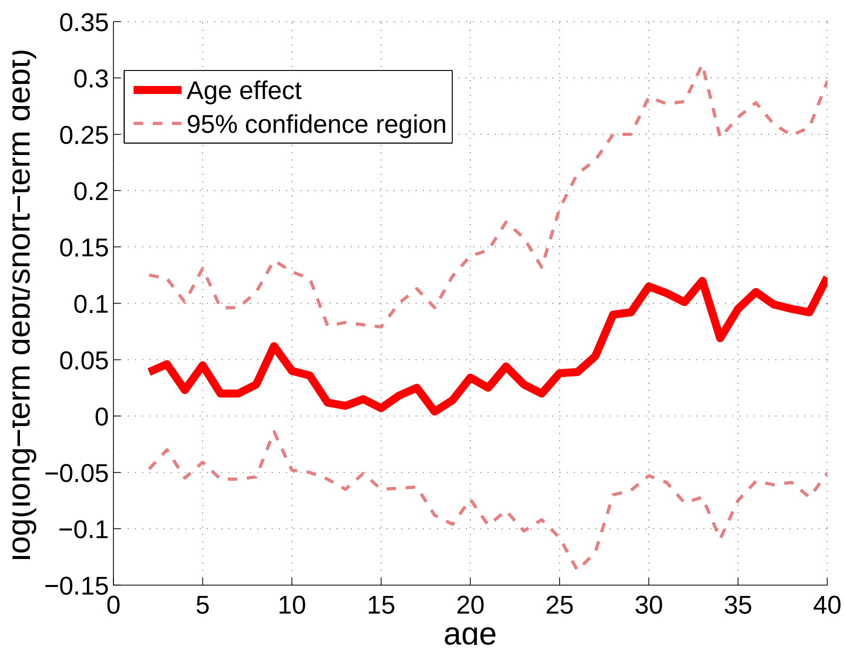
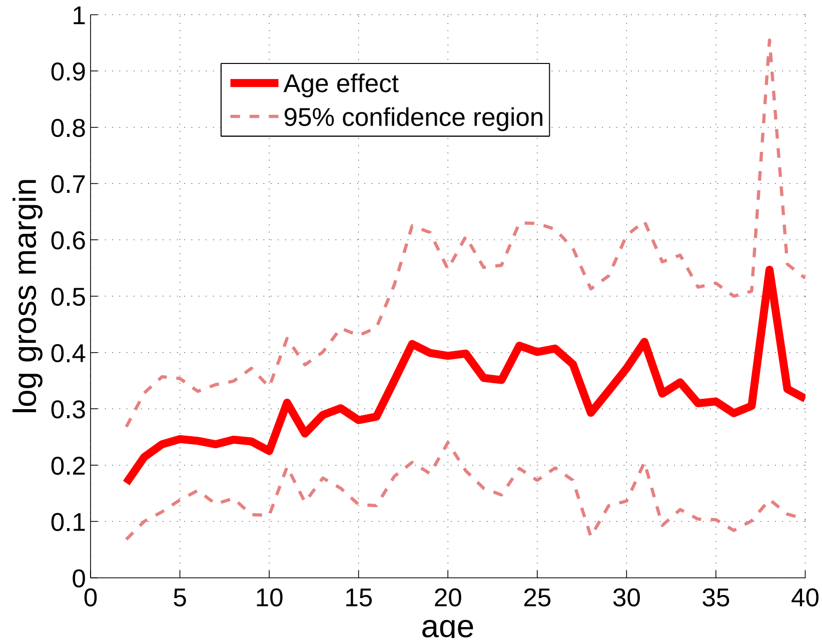


(b)

Notes: Age effects are estimated using the Deaton (1997) decomposition. See the text for more details.

Figure 4: Unconditional life-cycle profile of mark-ups



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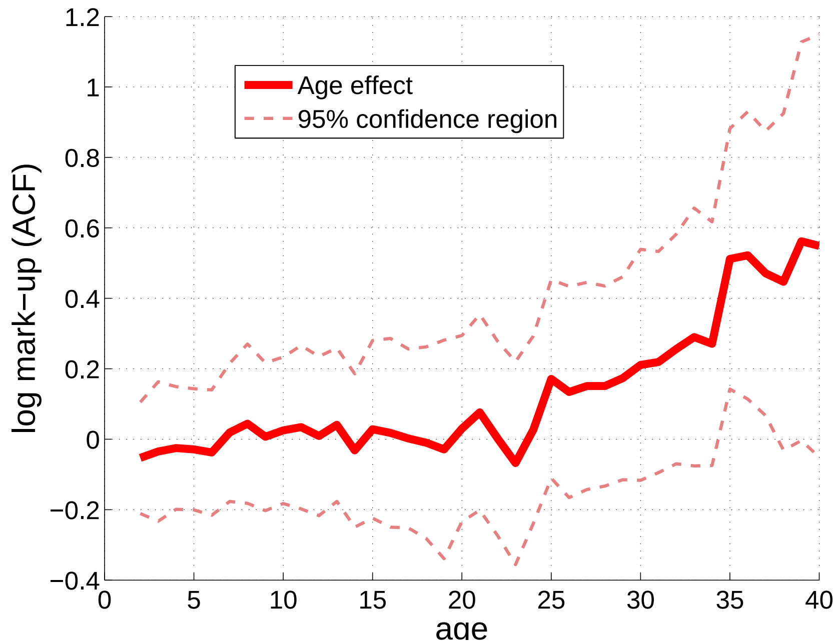
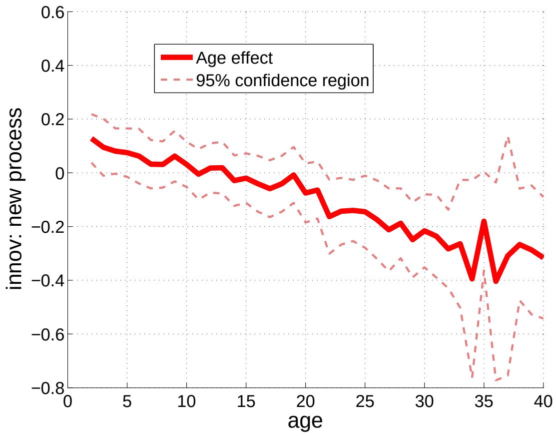


(b)

Notes: Age effects are estimated using the Deaton (1997) decomposition. See the text for more details.

Figure 5: Unconditional life-cycle profile of different types of innovation.



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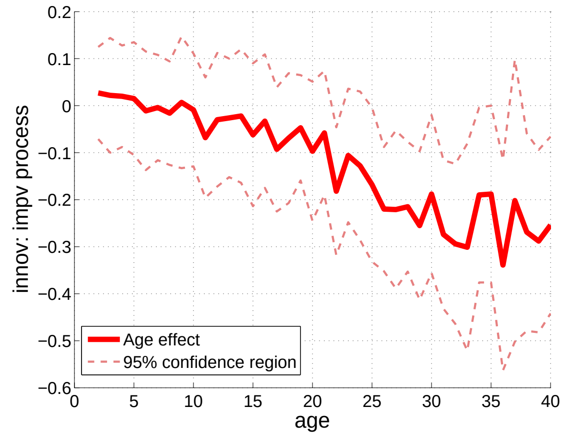

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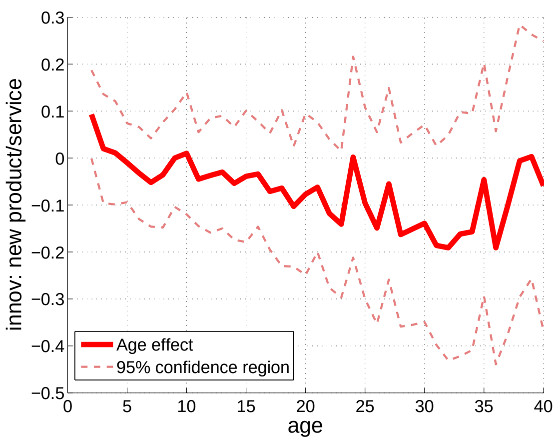

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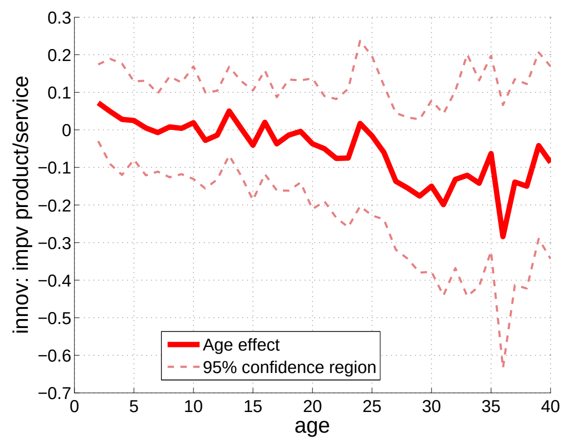
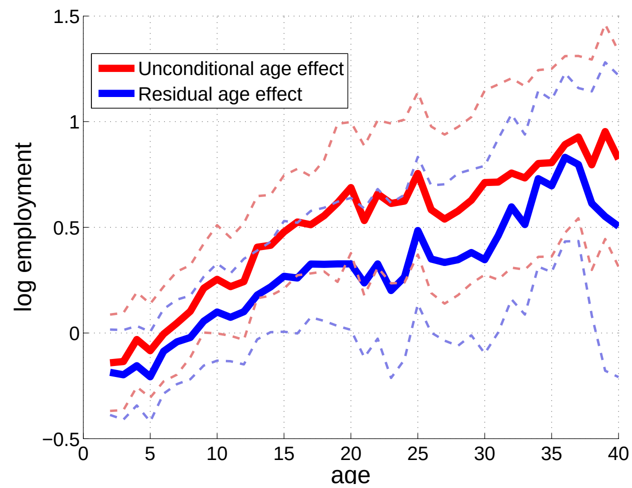


(d)

Notes: Age effects are estimated using the Deaton (1997) decomposition. See the text for more details.

Figure 6: Residual vs. unconditional dynamics of size and exit



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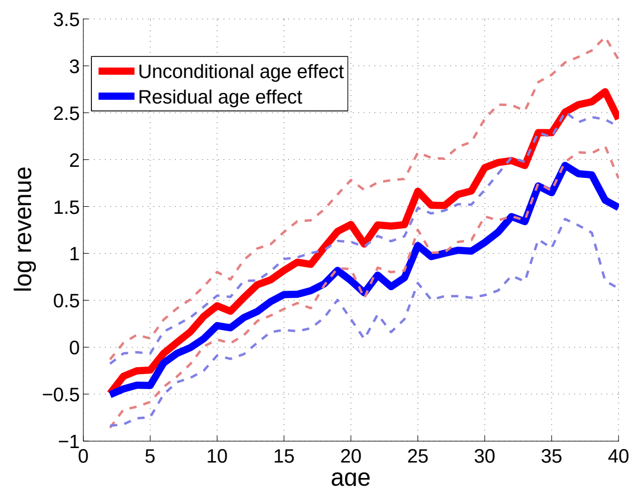

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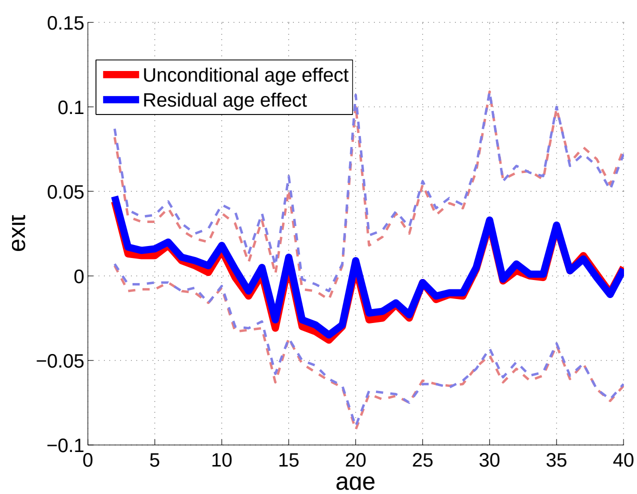

(c)

Notes: Age effects are estimated using the Deaton (1997) decomposition. See the text for more details.