From Employee to Entrepreneur: The Role of Employer Size on Spinout Dynamics*

Faisal Sohail†

University of Melbourne

January 2020

Abstract

Most new firms are founded by former employees of existing firms – *spinouts*. This paper documents how employer size shapes the entry and post-entry dynamics of spinouts. Using micro-data from Mexico, I show that employees from small firms are more likely to form spinouts than employees of large firms. In addition, spinouts from large employers start at a larger scale and grow faster than spinouts from small employers. I argue that this results from employees learning from their employers and develop a model of occupational choice and firm dynamics which operationalizes this theory. Using a calibrated version of the model, I analyze the aggregate implications of the link between employer size and spinout dynamics for macroeconomic outcomes both within and across economies. First, I argue that learning efficiency – interpreted as management quality – not only accounts for differences in spinout formation between the U.S. and Mexico, but also explains a sizeable share of the variation in the firm size distribution and output per worker. Second, I show that employee learning has meaningful and long-term implications on the creation of *new* firms in response to policies that target *existing* firms. Taken together, this paper establishes a connection between incumbent and entrant firms and shows that it is important for aggregate outcomes.

Keywords: spinouts, firm dynamics, occupational choice, learning, management

JEL Codes: J24, L25, O11, D83

*For their support and guidance, I thank Yongseok Shin and Alexander Monge-Naranjo and Ping Wang. For helpful comments and suggestions, I would also like to thank Brian Bergfeld, Paco Buera, Chris Edmond, Markus Posckhe, Lin Shao, Lawrence Uren and Emircan Yurdagul, and seminar participants at the University of Alberta, University of Melbourne, 2018 Spring Midwest Macro Meetings and the Bank of Canada. Earlier versions of this paper circulated under the title "Employer Size and Spinout Dynamics".

†Department of Economics, University of Melbourne. FBE Building, Carlton, VIC, 3053. Email: faisal.sohail@unimelb.edu.au

1 Introduction

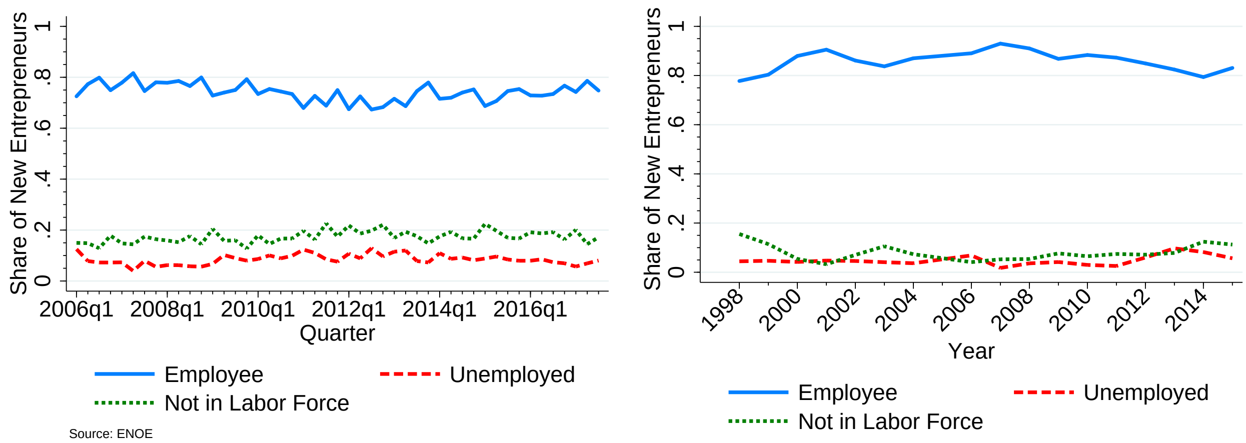
New firms contribute significantly to the economy. For instance, recent studies emphasize their impact on employment dynamics and productivity growth in both developed and developing economies.[1] However, as shown in Pugsley et al. (2019), not all new firms contribute equally, with only few entrants growing quickly while most others remain small, or exit. Hence, understanding what determines the quantity and quality of new firms is important for understanding macroeconomic outcomes both within and across economies. In this paper, I document how existing firms shape the entry and post-entry dynamics of new firms and then study the aggregate implications of this relationship. To do this, I focus on an important subset of new firms – *spinouts*.

Spinouts are business ventures founded by former employees of existing firms. They account for the majority, around 80%, of all new entrepreneurs in both Mexico and the United States (see figure 1).[2] Using micro-data from Mexico, I establish a relationship between employer productivity – proxied by the number of employees – and spinout entry, size and growth. By tracking transitions from employment to entrepreneurship, I find that employees of smaller firms are much more likely to start their own firm compared to employees of larger firms. On the other hand, using firm-level data, I show that firms founded by former employees of larger firms are, on average, more productive and grow faster than firms founded by former employees of smaller firms. That is, the size of an employer is *negatively* correlated with spinout entry and *positively* correlated with spinout performance and growth.

This relationship is robust to a variety of employer and individual controls and is not driven by differences in separation rates or income by employers of varying sizes. Additionally, I argue that these findings cannot be explained wholly by theories of selection and present evidence consistent with a theory of knowledge diffusion between employees and employers. A qualitatively similar relationship exists in data for the United States (U.S.). However, there are large quantitative differences in spinout entry, with employees in Mexico three times more likely to form spinouts

[1] See for example Haltiwanger et al. (2013) on the role of young firms on employment dynamics in the U.S. Foster et al. (2001) also provides evidence for the U.S. on the relationship between productivity growth and firm entry. Asturias et al. (2019), and the references therein , provide similar evidence for a number of developing economies.

[2] *Spinoffs* are distinct from spinouts as spinoffs typically refer to those firms that are i) founded by employees and ii) operate in the same industry as their previous employer. Throughout this paper, I will refer to spinouts as all firms founded by former employees of existing firms regardless of whether or not they operate within their previous employer's industry.



(a) Mexico

(b) United States

Figure 1: Share of New Entrepreneurs by Prior Status in Labor Force

Notes: The figure plots the share of individuals that transition into entrepreneurship from either i) employment, ii) unemployment or iii) out of the labor force between two consecutive years. Details on the data are described in appendix A.

than those in the U.S.

To study the aggregate implications of the relationship between employer size and spinout dynamics, I build a general equilibrium model of occupational choice and firm dynamics. In the model, agents are heterogeneous in entrepreneurial productivity and choose between employment and entrepreneurship. Entrepreneurs hire workers and make risky investments to improve their productivity. Workers are employed by entrepreneurs and can learn from their employers in order to improve their own productivity and potentially form spinouts. A unique feature of this model is the structure of learning. It assumes that both the cost and benefit of learning are increasing in the employer-employee productivity gap. This captures the intuitive notion that highly productive workers are better able to learn from employers and that there is more to learn from highly productive employers. This structure endogenizes new firm entry with characteristics of existing employers determining characteristics of future entrants – a channel novel to models of occupational choice and firm dynamics.

When calibrated to match salient features of the Mexican economy, the model's stationary equilibrium replicates the observed empirical evidence. A negative relationship between employer size and spinout entry is generated by the cost of learning increasing with employer productivity. The model also matches the positive relationship between employer size and spinout performance as employees of larger firms learn more from their employer. Spinout growth and employer size are also positively associated and this relationship is driven by the option value of learning in employment. In particular, the option of learning as a *worker*, lowers the incentives for *entrepreneurs* to innovate, especially for low productivity entrepreneurs. This means that productive firms invest relatively more in growth. As a result, spinouts from larger firms will, on average, start large and grow faster than spinouts from smaller firms, as observed in the data.

I use the calibrated version of the model to conduct two quantitative exercises which emphasize the aggregate importance of the relationship between employer size and spinout dynamics.

The first exercise investigates the factors driving the high rate of spinout entry in Mexico relative to the U.S. Two potential factors are considered; i) investment cost and ii) the efficiency with which workers learn from employers. Differences in investment cost are interpreted as capturing well-established institutional differences that affect incumbent firms. Learning efficiency is interpreted as representing managerial practices, with better practices – as exist in the U.S. – increasing the amount that employees can learn from employers.[3] The analysis shows that differences in investment cost alone are not large enough to fully explain the three-fold difference in spinout entry rate between U.S. and Mexico. Instead, improved learning efficiency is also necessary. In addition to being crucial for spinout formation, learning efficiency also accounts for a sizeable share of unexplained variation in output per worker, the share of entrepreneurs and average firm size. Counter-intuitively, the model implies that improving learning efficiency leads to a *decrease* in spinout entry. This is due to a general equilibrium effect; improving employee learning increases the return to employment and endogenously shifts the firm size distribution to the right. The resulting firm size distribution features higher productivity employers from whom it is costlier to learn, lowering the spinout rate. However, while there are fewer spinouts, those employees that are able to form spinouts operate higher quality firms.

The second quantitative exercise explores the impact of a temporary reform – a subsidy to small firms – on new firm entry. The benchmark model's response to this policy is compared to that of a version of the model without employee learning, that is when employer size and spinout dynamics are independent. I find stark differences in the transitional dynamics across these two

[3] See, for example, Bloom and Van Reenen (2007) for evidence on cross-country variation in management practices.

frameworks. In addition to featuring longer transitions, the benchmark economy predicts the opposite impact on the number and average productivity of entrants compared to the more standard model without learning. This difference is due to the temporary reallocation of workers towards smaller firms which has long-lasting implications in the model where entrants are endogenous to employer characteristics. This analysis has implications for policy design since it shows that policies targeting existing firms will have a meaningful and long-term impact on the creation of new firms.

Taken together, this paper identifies and emphasizes the important relationship between incumbent firms and the quantity and quality of entrants.

An outline of the paper is as follows. A review of the literature is provided below followed by section 2 which details the empirical evidence for Mexico. Section 3 presents the model. Sections 4 and 5 describe the model calibration and the stationary equilibrium, respectively. Section 6 outlines the interpretation and results of the quantitative exercises and section 7 concludes the paper. Evidence from the U.S. along with details of the data is presented in the data appendix.

Related Literature This paper contributes to several strands of literature. First, I add to and extend the existing empirical literature on spinout entry and its relationship with employer characteristics. Country level studies include, Sørensen and Phillips (2011) (Denmark),Elfenbein et al. (2010) (U.S.), Muendler et al. (2012)(Brazil), Berglann et al. (2011) (Norway), and Andersson and Klepper (2013) (Sweden). These studies are based primarily on matched employer-employee data and also document a negative relationship between employer size and spinout entry. Existing research on the relationship between employer size and spinout performance is more limited and with mixed results. This paper is the first to use firm level data to study the performance of spinouts up to 20 years after entry.[4] In addition, this paper is the first to study spinouts in Mexico. An important advantage of using Mexican data is that it includes detailed information on individual demographics and work related variables. This allows me to uncover novel relationships between spinout formation and characteristics such as job tenure, age, and income among others. Furthermore, these data include information on both formal and informal activity – an important distinction in developing economies. This more comprehensive coverage allows for cross-country

[4] Andersson and Klepper (2013) is most closely related: using matched employer-employee data from Sweden, they find a positive relationship between employer size and spinout performance up to 12 years after entry.

comparisons of spinout dynamics and their implications for aggregate outcomes.

This paper also relates to the literature on knowledge diffusion between employers and employees, and the formation of spinouts. Early works include Franco and Filson (2006) who also focus on the ability of employees to learn from their employers but do not study aggregate implications resulting from this. Most closely related is Baslandze (2017) who extends their framework and studies the interaction of non-compete laws, innovation incentives of existing firms and economic growth. Similar to Baslandze (2017), the framework developed in this paper also features a tradeoff between the intensity of firm level investment and spinout formation. However, it does so through an alternative mechanism – the option value of learning.[5] In addition, both Franco and Filson (2006) and Baslandze (2017) focus on a single industry or a narrow set of firms within an industry and document a *positive* relationship between spinout entry and employer size.[6] The resulting theoretical models replicate this positive relationship which is not observed in this and other country level studies in the literature.

The model in this paper introduces employee learning in an occupational choice framework which features firm dynamics. Learning here is distinct from existing works such as Roys and Seshadri (2014) and Lucas and Moll (2014) since I assume that it is not only a function of an agent's own productivity but also that of their employer. Theoretical work from Chari and Hopenhayn (1991), Dasgupta (2012) and Jovanovic (2014) introduce learning where both worker and employer productivity is important but abstract from new firm dynamics and focus on technology adoption, gains from trade and economic growth, respectively. The empirical evidence and theoretical implications from the model developed in this paper are consistent with those of Jarosch et al. (2019) who use administrative level data from Germany and find strong evidence in support of employees learning from co-workers, particularly those in managerial positions. The empirical findings in this paper also provide a potential source for the ex-ante heterogeneity among new firms recently highlighted by Pugsley et al. (2019).

Finally, this paper has implications for policy design. Of particular relevance is the growing lit-

[5] In Baslandze (2017), firms face a tradeoff between investment and the possibility of employees spinning out and competing with incumbents. Here, agents face a trade-off between investing in their productivity as entrepreneurs or learning from their employers as workers. This lowers the incentive for investment for marginal entrepreneurs.

[6] Franco and Filson (2006) use data from the rigid disk drive industry. Baslandze (2017) focuses on only those firms that issue patents as sources of spinouts.

erature that studies the impact of management practices on firm level and aggregate outcomes. Much of this literature investigates the role of management through randomized controlled trials (e.g. Abebe et al. (2019); Brooks et al. (2016); Bruhn et al. (2018); Bloom et al. (2013)). The empirical and theoretical findings in this paper imply that the impact of improving management practices within existing firms is relevant for the creation, size and growth of new firms. While this holds true for a broad set of policies, it is particularly relevant for interventions aimed at improving management practices since these practices may have a role in improving employee learning and hence shape the relationship between existing firms and new firms.

2 Empirical Evidence

This section details the empirical evidence on spinout entry, performance and exit in Mexico. Analogous evidence based on U.S. data is reported in section A.2 of the appendix.

Data Description Individual level data is taken from the 2005Q1 to 2018Q3 National Survey of Occupation and Employment (*Encuesta Nacional de Ocupación y Empleo*, ENOE) conducted in Mexico. The ENOE survey is a nationally representative survey and is a close analogue to the Current Population Survey (CPS) conducted in the US in both the questions asked and its design. Like the CPS, the ENOE serves as an important resource in measuring the status of Mexico's labor force.[7] Participants in the ENOE are interviewed for at most 5 times over 5 consecutive quarters. By exploiting the rotating panel nature of this survey, individuals are matched across quarters to track flows between employment, entrepreneurship and non-employment.[8] Spinouts are identified as those individuals who transition from full time employment in private, non-agricultural occupations in quarter q of year y to entrepreneurship (either with or without employees) in the same quarter of the following year. Since this paper focuses on firms founded by former employees, I exclude respondents who experience any periods of non-employment in intervening quarters. Respondents

[7] Additional details and microdata are available at http://www.inegi.org.mx/

[8] The matched sample is constructed by tracking respondents across a calendar year. That is, I match responses from an individual's first interview in quarter q of year y to their fifth interview in quarter q of year $y + 1$. Using data from 2005Q1 to 2018Q3 the average match rate is 80% and the sample. Throughout this paper, I use the terms self-employment and entrepreneurship interchangeably.

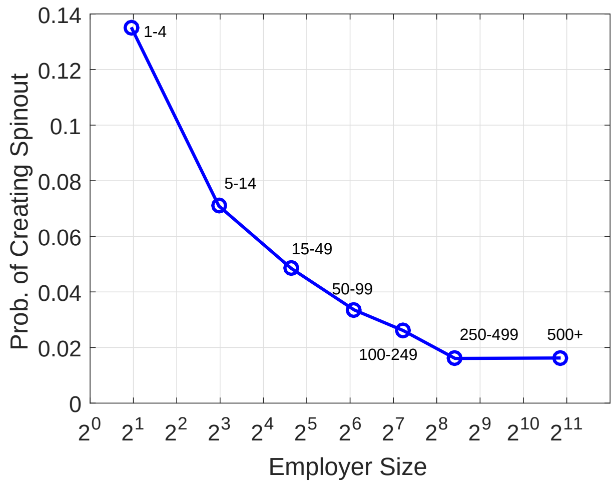


Figure 2: Probability of Entering as Spinout

Notes: The sample uses data from the matched ENOE sample covering 2005Q1 to 2016Q3 and includes full-time, male, private, non-agricultural employees aged between 18 and 65. The average firm size for the 1 to 4 employee size category is computed using the 2012 ENAMIN. The averages for all other firm size categories are computed assuming that the firm size distribution follows a Pareto distribution with tail parameter 1.24. This tail parameter is estimated using data from the 2006 and 2010 World Bank Enterprise Surveys for Mexico and the method detailed in Axtell (2001).

that report being involuntarily separated from employment are also excluded. The final sample includes over 2 million survey responses from over 574,000 individuals.

Firm level data comes from the National Survey of Micro-Businesses *(Encuesta Nacional de Micronegocios*, ENAMIN) and includes information covering four years between 2002 and 2012.[9] Participants in the ENAMIN are firm owners that have up to 15 employees if in the manufacturing sector and up to 10 employees otherwise.[10] The survey includes detailed questions about the firm's activities, as well as the founder and their prior work history. Spinouts are identified as those firms that were founded solely by former employees who voluntarily left their prior position. The sample includes only former employees that were employed in private, non-agricultural sectors and earned at least the mandated minimum wage. Additional details on the ENAMIN sample are described in the appendix.

[9] The ENAMIN was conducted in 1992, 1994, 1996, 1998, 2002, 2008, 2010 and 2012.

[10] In the ENOE sample 95.3(97.5)% of all employers hire at most 10(15) employees. This is in broadly in line with Hsieh and Olken (2014) who use census data on manufacturing firms and find that 91.7% of all firms in Mexico hire at most 9 employees. ENAMIN surveys prior to 2002 were conducted in 1992, 1994 1996 and 1998 and include only firms which have up to 5 employees if not in the manufacturing sector. For this reason, the empirical analysis is based on the 2002 to 2012 ENAMIN samples. The earlier samples are used to construct sample shares in figure A.3 below.

2.1 Spinout Entry

Figure 2 plots the relationship between the probability of starting a spinout and employer size in the matched ENOE sample. The vertical axis shows the share of employees that transitioned to entrepreneurship within a year without any intervening spells of non-employment while the horizontal axis reports the average employer size for each size bin reported in the ENOE.

Importantly, the relationship in figure 2 is robust to controls for occupation, industry, informality in employment, demographic characteristics, state and year fixed effects. More formally, I estimate the following probit regression:

$$P_{ist} = \alpha + \sum_s \beta_s D_{st} + \gamma \tilde{y_{ist}} + \delta h_{ist} + \mathbf{X}_i + \mathbf{Z} + \epsilon_{ist} \tag{1}$$

where P_{ist} is an indicator variable which is equal to 1 if an employee i working for an employer of size s forms a spinout between year t and $t+1$ and 0 otherwise. D_s is an indicator of employer size categories. $\tilde{y}_{ist}$ is the conditional income earned by i while employed. h_{ist} is the number of years i was employed with their previous employer. The variables $\mathbf{X}_i$ controls for individual and occupation characteristics, while $\mathbf{Z}$ controls for year, state, industry, and informality fixed effects (in current and prior occupation). Table 1 describes the controls in detail and reports the marginal impact of firm size on spinout entry. From column (1), workers of employers with up to 4 employees are 9% more likely to form spinouts than workers of employers with at least 50 employees, and this relative propensity declines monotonically as employer size increases.

Next, I identify potential mechanisms driving the negative relationship between spinout entry and employer size. In the data appendix, I show that the relationship between employer size and spinout entry is similar in the U.S. This suggests a common phenomenon driving the negative relationship between spinout entry and employer size across these two countries. Existing research has distinguished between theories of selection and treatment of employment (e.g. Elfenbein et al. (2010)). Each has distinct predictions that can be empirically tested in the ENOE data.

I begin by testing for theories of selection. That is, the theory that individuals sort themselves into firms of different sizes based on ability or preference for entrepreneurship. An important prediction

Table 1: Marginal Effects of Employer Size on Probability of Entry as Spinout

	(1) P_i	(2) P_i	(3) P_i
Employer Size			
▷ 1 to 4	0.088***	0.093***	0.093***
	(0.003)	(0.003)	(0.006)
▷ 5 to 9	0.052***	0.054***	0.051***
	(0.003)	(0.003)	(0.005)
▷ 10 to 14	0.032***	0.033***	0.030***
	(0.004)	(0.004)	(0.006)
▷ 15 to 49	0.019***	0.020***	0.023***
	(0.002)	(0.002)	(0.004)
Conditional Income in Employment	-	0.021***	0.023***
	-	(0.002)	(0.004)
Tenure with Employer (years)	-	-	0.002***
	-	-	(0.000)
Individual Controls	Y	Y	Y
Industry, State, Year Controls	Y	Y	Y
Pseudo R^2	0.110	0.112	0.129
N	190,831	190,673	66,313
Observed p	0.067	0.067	0.067

Notes: The omitted variable for employer size is the dummy for those employers with at least 50 employees. All probit regressions control for industry, year, and state fixed effects. Individual controls include i) quadratic in total years of experience, ii) four education bins which correspond to those with less than a HS degree, those with a HS degree, those with at least a college degree, and those with at least a HS but no college degree iii) indicator for those in managerial positions, iv) indicator for informality of most recent employer. When including tenure with employer as a regressor, I adjust the years of experience control to be equal to total years of experience excluding those with most recent employer. Data on job tenure is only available in the extended ENOE sample which has been conducted once a year since 2006. Standard errors are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1

of such theories is that controlling for ability can account for the negative relationship between spinout formation and employer size. To test this, I include a proxy for unobserved ability in specification (1); the conditional income earned while employed. Column (2) reports the marginal impact of this variable on spinout entry.[11] Including this measure of ability does not overturn the negative relationship between employer size and spinout entry, suggesting little support for selection based on ability. Indeed, a 1% increase in conditional income is associated with a 2 percentage point increase in the likelihood of spinout entry.

The ENOE data does not allow testing for selection based on other (unobservable) characteristics such as risk tolerance or preference for being one's own boss.[12] Instead, I provide empirical support for a treatment theory of employment – namely that employees learn from their employers while

[11] Conditional income is computed as the residual from a regression of log monthly income on i) four dummies of years of completed education (0-12, 12, 13-16, and 16+) ii) year, state and industry, fixed effects and iii) a quadratic in years of total experience computed as age minus 6 minus years of schooling. Using unconditional income yields quantitatively similar results.

[12] Non pecuniary factors such as these have been highlighted as influencing entrepreneurship in Hurst and Pugsley (2015) among others.

employed and this drives spinout entry. A prediction of this theory is that additional time in employment makes learning and hence spinout formation more likely. In other words, we expect a positive relationship between tenure with employer and spinout entry. On the other hand, a theory of selection would predict no relationship between tenure and spinout entry. Column (3) of table 1 reports the marginal impact of tenure with employer, and finds a positive and statistically significant relationship with spinout entry; an additional 5 years with an employer leads to a 1 percentage point increase in the likelihood of spinout entry.

To lend further support for a treatment effect of employment, I test whether the impact of tenure on spinout entry varies by employer size. Since we know from table 1 that smaller firms are more likely to generate spinouts, a theory of employees learning would imply that the impact of tenure on spinout entry is strongest in smaller firms. I show this is indeed the case by estimating specification (1) separately for each employer size category. Table 2 reports the results: an additional 5 years of employment in smaller firms leads to a 1 percentage point increase in the likelihood of employees forming spinouts relative to employment in larger firms. The impact of conditional income is also stronger in relatively smaller firms suggesting that employees with higher unobserved ability are more likely to learn in smaller firms. I take this as evidence supporting a theory of employees learning in employment and use these findings to guide my modeling choices.

Table 2: Marginal Impact of Conditional Income and Tenure by Employer Size

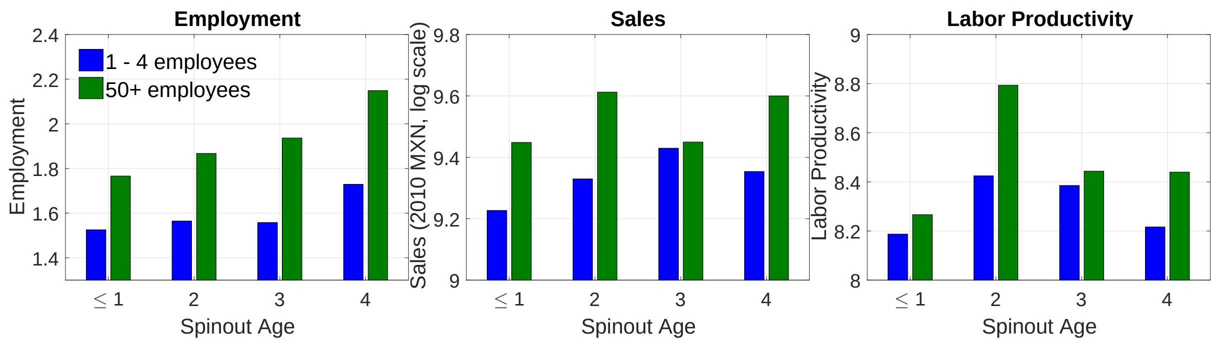
	1 to 4	5 to 9	10 to 14	15 to 49	50+
Conditional Income in Employment(y_i)	0.0382***	0.0425***	0.0174	0.0244***	0.0089***
	(0.0102)	(0.0114)	(0.0112)	(0.0068)	(0.0029)
Tenure with Employer (years) (h_i)	0.0059***	0.0019***	0.0022***	0.0004	0.0001
	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0002)
Pseudo-R^2	0.053	0.092	0.161	0.088	0.088
N	19,968	8,029	4,017	12,583	21,690
Observed p	0.136	0.080	0.058	0.044	0.023

Notes: The table reports the marginal impact of conditional income and tenure with employer as estimated from the following regressions:

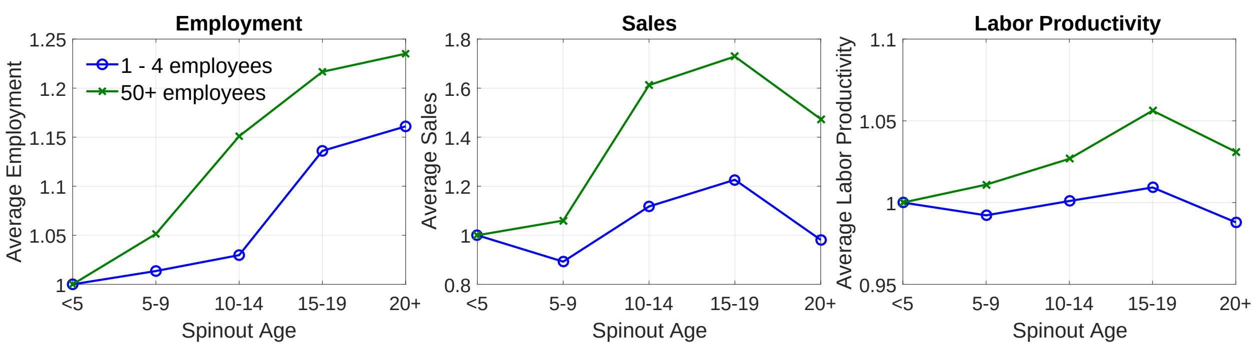
$$P_{ist} = \alpha + \gamma^s \tilde{y_{ist}} + \delta^s h_{ist} + \theta \mathbf{X}_i + \mathbf{Z} + \epsilon_{ist} \forall s$$

where s indexes employer size categories in the ENOE sample and the variable definitions are as in specification (1). Standard errors are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1

It is possible that the negative relationship between spinout entry and employer size is due to the higher opportunity cost of pursuing entrepreneurship in larger firms. This is quite plausible as large firms offer an income premium (see e.g. Colonnelli et al. (2018)). Evidence in support



(a) At Entry



(b) Over the Lifecycle

Figure 3: Spinout Performance by Previous Employer Size

Notes: Data is from the ENAMIN sample and includes male founders aged between 18 and 65 of firms engaged in full-time, private, non-agricultural activities. Panel (a) plots the level of average employment, sales and labor productivity for firms founded by former employees of small (blue) and large (green) firms. Panel (b) normalizes the initial size of spinouts to 1 and plots the average employment, sales and labor productivity over the spinout's life cycle conditional on survival.

of this theory would require that the likelihood of spinout entry declines with income earned in employment. However, as shown above, this is not the case - higher conditional income is associated with higher probability of spinout entry within firm size categories as well as in the aggregate.[13]

In the data appendix, I show that the findings on spinout entry are not driven by differences in separation rates of firms of different sizes (see e.g. Donovan et al. (2018)). I also show that the negative relationship between spinout entry and employer size is evident across industries and occupations. Restricting the definition of spinouts to only include those self-employed and also employ others yields qualitatively similar results.

2.2 Spinout Size

In this section, I document the relationship between employer and size spinout size using firm level data from the ENAMIN. Figure 3 reports average employment, sales and labor productivity

[13]Results are qualitatively similar when including unconditional income as a regressor.

of spinouts by prior employer size. I group employer sizes into two categories and study those spinouts that were spawned from small employers, with 1-4 employees, and large employers, with over 50 employees. Panel (a) reports the spinout size in the initial four years of operation and shows that, *at entry*, spinouts from large firms are 10-30% larger than spinouts from small firms. Panel (b) reports spinout growth relative to initial size, and shows that a performance advantage persists over the spinout's life cycle; with spinouts from smaller firms experiencing flatter age-size profiles. These simple cross-sectional averages suggest that there is a *positive* relationship between employer size and spinout performance not only at entry but also over the life cycle.

I test this relationship with more rigor by controlling for a number of important characteristics of the spinout and its founder. In particular, I estimate the following regression:

$$Y_{isat} = \alpha + \sum_{s} \beta_s D_{ist} + \sum_{a} \gamma_a \tilde{D}_{iat} + \sum_{s,a} \delta_{s,a} \left(D_{ist} \times \tilde{D}_{iat} \right) + \theta \mathbf{X}_i + \mathbf{Z} + \epsilon_{isat} \qquad (2)$$

where the dependent variable is the performance measure of a spinout of age a in year t founded by an individual i that was previously employed with an employer of size s.[14] The vector $\mathbf{X}_i$ controls for the founder's potential years of experience, residual income in employment, tenure with previous employer and an indicator for whether spinout is in the same industry as the founder's previous place of employment. $\mathbf{Z}$ captures year, state, cohort and spinout industry (2 digit NAICS codes) fixed effects. The variable D_{ist} is defined as in specification (1) with $\tilde{D}_{iat}$ analogously categorizing spinout age into three categories. The interaction term $\left(D_{ist} \times \tilde{D}_{iat} \right)$ is included to capture the difference in spinout size at different ages based on previous employer size. In particular, the coefficient $\delta_{s,a}$ reports the size difference between spinouts from employers of size s at age a relative to a reference group. When the reference group is spinouts from small employers at entry (i.e. age 0), the coefficient β_s reports the initial difference at entry in performance for spinouts from employers of size s. From figure 3 we expect both $\delta_{s,a}$ and β_s to be positive and increasing in previous employer size s and spinout age a - that is, spinouts from larger employers grow faster than those from smaller employers at each point in their life cycle.

[14] Six measures of spinout size are computed; i) number of employees, ii) owner's income, iii) wage bill, iv) capital stock, v) sales and vi) labor productivity. Labor productivity is measured as the net profit per worker where net profit is defined as the difference between sales, total revenue and the wage bill.

Table 3: The Impact of Employer Size on Spinout Size over the life cycle

	(1) Employees	(2) Income	(3) Wage Bill	(4) Capital Stock	(5) Sales	(6) Labor Prod.
	Panel A: Baseline					
Employer Size						
▷ 5 - 49 emp	0.217***	0.169***	0.306***	0.151	0.157**	0.054
	(0.076)	(0.045)	(0.066)	(0.110)	(0.066)	(0.117)
▷ 50+ emp	0.169**	0.128**	0.216***	0.278**	0.161**	0.069
	(0.084)	(0.050)	(0.074)	(0.122)	(0.075)	(0.130)
Spinout Age						
▷ 5 - 9 yrs	-0.201*	-0.121*	-0.043	-0.477***	-0.270***	-0.167
	(0.113)	(0.066)	(0.096)	(0.162)	(0.100)	(0.174)
▷ 10 - 14 yrs	-0.449***	-0.116	-0.047	-0.486**	-0.266*	-0.187
	(0.161)	(0.094)	(0.138)	(0.233)	(0.142)	(0.241)
▷ 15+ yrs	-0.397*	-0.284**	0.067	-0.777**	-0.464**	-0.354
	(0.214)	(0.126)	(0.181)	(0.307)	(0.188)	(0.319)
Employer Size × Spinout Age						
▷ 5 - 49 emp × 5 - 9 yrs	0.250**	0.036	0.092	0.363**	0.242**	0.260
	(0.116)	(0.069)	(0.099)	(0.167)	(0.102)	(0.178)
▷ 50+ emp × 5 - 9 yrs	0.065	0.137*	0.020	-0.003	0.267**	0.188
	(0.129)	(0.076)	(0.111)	(0.189)	(0.115)	(0.202)
▷ 5 - 49 emp × 10 - 14 yrs	0.137	-0.017	-0.032	0.168	-0.005	0.232
	(0.122)	(0.071)	(0.103)	(0.177)	(0.106)	(0.182)
▷ 50+ emp × 10 - 14 yrs	0.242*	0.065	0.228*	0.338*	0.136	0.194
	(0.137)	(0.081)	(0.117)	(0.197)	(0.122)	(0.209)
▷ 5 - 49 emp × 15+ yrs	0.251**	0.056	-0.073	0.419***	0.126	0.124
	(0.102)	(0.060)	(0.087)	(0.151)	(0.090)	(0.155)
▷ 50+ emp × 15+ yrs	0.234**	0.159**	0.125	0.394**	0.241**	0.414**
	(0.112)	(0.067)	(0.097)	(0.167)	(0.100)	(0.171)
Industry FE	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
N	5,616	5,080	4,006	3,922	4,869	3,101
R^2	0.069	0.136	0.086	0.210	0.101	0.069
	Panel B: With controls					
Indicator for Same Industry	0.171***	0.142***	0.087*	0.102	0.218***	0.158**
	(0.052)	(0.029)	(0.045)	(0.073)	(0.044)	(0.076)
Conditional Income in Employment	0.132***	0.169***	0.177***	0.243***	0.213***	0.198***
	(0.029)	(0.017)	(0.025)	(0.042)	(0.026)	(0.043)
Tenure with Employer (years)	-0.009	-0.000	-0.009	0.022*	0.002	-0.003
	(0.009)	(0.005)	(0.008)	(0.013)	(0.008)	(0.013)
N	3,114	2,873	2,227	2,191	2,824	1,825
R^2	0.086	0.169	0.112	0.255	0.141	0.105

Notes: Data is from the 2002-2012 ENAMIN samples. Panel A displays displays the coefficients from the following OLS regression: $Y_{isat} = \alpha + \sum_s \beta_s D_{ist} + \sum_a \gamma_a \tilde{D}_{iat} + \sum_{s,a} \delta_{s,a} \left(D_{ist} \times \tilde{D}_{iat} \right) + \theta \mathbf{X}_i + \mathbf{Z} + \epsilon_{isat}$. Panel B reports the coefficients on job tenure and income in employment. Standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Panel A of table 3 reports baseline results from estimating (2). The omitted variables are the indicators for spinouts founded by employees of small firms (1 - 4 employees) and the indicator for spinouts younger than five years of age (0 - 4 yrs). First, the coefficient on spinouts from medium (5-49 employees) and large (50+ employees) employers is positive and statistically significant for 5 out of 6 measures of spinout performance, indicating that spinouts from larger employers are larger *at entry*. For instance, in their initial years spinouts from larger firms have a 30, 13 and 16% higher wage bill, income and sales, respectively.[15]

The coefficients on the interaction term show that this initial performance gap persists and indeed grows over the spinout's life cycle. As an example, mature spinouts (age 15+) from large firms have around 40% higher measured labor productivity relative to spinouts from small firms of the same age. Similarly, spinouts from medium sized firms have 36 and 42% higher capital stock than spinouts from smaller firms at an intermediate age (5 - 9 yrs) and mature age, respectively. Panel A is consistent with figure 3 - even after controlling for observable characteristics of the founder, industry, region and cohort, there is a positive relationship between spinout performance and previous employer size.

Notice that this positive relationship itself supports a view that employees learn from their employers. More specifically, interpreting employer size as a proxy for employer productivity, a theory of knowledge diffusion predicts that employees working - and learning - from more productive employers would then in turn be more productive when operating their own enterprises.[16] Having said this, a positive relationship would also be predicted by a theory of selection in which there is positive sorting between workers and employers. To distinguish between these competing theories, I provide further evidence consistent with learning in panel B of table 3.

First, I test whether spinouts that remain in the same industry as their previous employer perform better than those that do not. In the ENAMIN sample, only one-third of spinouts remain in the same (4-digit) industry as their previous employer.[17] The first row of panel B shows that spinouts

[15]The coefficient for medium (5 to 49) and large (50+) employers are not statistically different from each other for any of the regressions.

[16]A strong, positive correlation between measures of firm size and measured productivity has been identified in a number of studies. See for example Foster et al. (2008) and Leung et al. (2008) for evidence from the U.S. and Canada, respectively.

[17]When measured at the 2-digit level, around two-thirds of all spinouts opeate in the same industry as their previous employer.

remaining in the same industry tend to be 10% to 20% larger than those that switch industries. The positive impact of remaining within an industry is consistent with the existing literature and is interpreted as reflecting a transfer of industry specific know-how that employees learn from their employer and utilize in their spinout.[18]

Including job tenure and conditional income in employment as explanatory variables yields results similar to those found for spinout entry. Job tenure has a positive and statistically significant impact on only the capital stock of spinouts and a statistically insignificant impact on other measures. The impact of conditional income is positive and statistically significant for all measures of spinout size with higher conditional income having a much larger impact on spinout size than tenure. This evidence points to the importance of employee learning as well as employee ability on spinout performance. As such, any theory of spinouts should incorporate both factors.

Before discussing the relationship between spinout exit and employer size, it should be noted that the ENAMIN sample only includes firms with at most 15 employees. While this accounts for the bulk of firms in Mexico, it is problematic as some spinouts may grow to be ineligible for inclusion in the ENAMIN over their life cycle. Of particular concern is the possibility that spinouts from small employers grow at *faster* rates than those from large employers and hence leave the ENAMIN sample at faster rates. To address this concern, I use qualitative responses to show that spinouts from smaller firms have lower growth expectations that those from larger firms at each point in their life cycle (see figure A.4in the appendix). Further, I show that, in the ENAMIN sample, the share of spinouts from small (large) employers rises (falls) over the life cycle which is inconsistent with the possibility that spinouts from small firms leave the ENAMIN sample at higher rates (see figure A.3 in the appendix).

2.3 Spinout Exit

The empirical analysis so far has ignored an important component of spinout dynamics: exit. Here, I study the relationship between employer size and likelihood of spinout exit. Unfortunately, neither the ENOE or ENAMIN are particularly well suited to this analysis. The former data only

[18] Andersson and Klepper (2013) also find a positive relationship between remaining in the same industry and spinout performance using data from Sweden.

allows for tracking individuals for up to four quarters after they form a spinout while the latter is a sample of surviving firms. Having said this, a well established fact is that exit rate declines with firm size; see for example Haltiwanger et al. (2013) and Clementi and Palazzo (2016). Given that spinouts from smaller firms tend to start and remain smaller than spinouts from larger firms, it is reasonable that spinouts from smaller firms also exit at higher rates. Despite their limitations, I test this relationship in the ENOE using the share of observed exit in the short panel of new spinouts.[19] The average exit rate in the ENOE data is around 40% per year, which is in line with evidence reported in Fajnzylber et al. (2006) for young, small firms in Mexico.

Table 4: Marginal Effects of Employer Size on Probability of Exit

	(1)	(2)
	P_i^{exit}	P_i^{exit}
Employer Size		
▷ 5 to 9	-0.129***	-0.107*
	(0.042)	(0.064)
▷ 10 to 14	-0.087*	-0.060
	(0.046)	(0.070)
▷ 15 to 49	-0.054	0.045
	(0.058)	(0.094)
▷ 50+	-0.025	-0.036
	(0.046)	(0.070)
Conditional Income in Employment	-	-0.008
	-	(0.039)
Tenure with Employer (years)	-	-0.004**
	-	(0.002)
Individual Controls	Y	Y
Industry, State, Year Controls	Y	Y
Pseudo R^2	0.044	0.075
N	6,256	2,115

Notes: The omitted variable the dummy for spinouts from small employers, that is those with 1-4 employees. The ENOE probit regressions are estimated following specification (1) with the dependent variable being probability of exit. Standard errors are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4 documents the results from estimating a probit regression under specification (1) using ENOE exit rates as the dependent variable. It shows that spinouts from larger firms are indeed less likely to exit than spinouts from smaller firms. However, the coefficients on previous employer size are not statistically significant for larger employers. Consistent with a theory of employee learning, years of tenure with previous employer is associated with a lower likelihood of exit - an additional 5 years of employment leads to a 2% decrease in exit probability. There is no statistically significant

[19] Construction of the measure of spinout exit is detailed in the appendix.

relationship between conditional income and exit although the coefficient is negative. These findings are in line with existing theory and evidence on firm exit and will be replicated in the theoretical model. In the data appendix, I test the relationship between employer size and spinout exit using qualitative responses from the ENAMIN sample and find no statistically significant relationship; see table A.3.

3 Model

The model economy consists of a unit continuum of agents that are heterogeneous in productivity. Agents are risk neutral and make an occupational choice in each period between wage employment and entrepreneurship as in the span of control framework of Lucas (1978). As entrepreneurs, agents utilize their productivity to hire workers, make risky investments in productivity and face idiosyncratic productivity shocks. This introduces both an endogenous and exogenous source of productivity evolution. As workers, agents are randomly matched with entrepreneurs, and choose how much effort to exert in order to learn from their employers and improve their productivity. Learning is costly and depends not only on the worker's productivity but also that of their employer. Those employees who are able to sufficiently learn from their employers transition out of wage employment and form spinouts. Employee learning introduces another endogenous source of productivity evolution and will be the focus of the quantitative analysis. The remainder of this section details the model and describes the stationary equilibrium.

3.1 Entrepreneur's Problem

Time is discrete and agents are heterogeneous in productivity z. As entrepreneurs, agents operate a decreasing returns to scale production function by hiring labor $l(z)$ at wage w which is determined in equilibrium. Profit $\pi(z)$ solves the following static maximization problem. :

$$\pi(z) = \max_l \; z^{(1-\eta)} l(z)^{\eta} - wl(z)$$

where $\eta \in (0, 1)$ determines the span of control of entrepreneurs. Notice, this production function implies that all workers contribute identically to production and hence, worker's marginal product is independent of their productivity.

Solving for the optimal labor choice yields both labor and profit as linear in productivity and is given by:

$$l(z) = z \left(\frac{\eta}{w}\right)^{\frac{1}{1-\eta}}$$

$$\pi(z) = z \left(\frac{\eta}{w}\right)^{\frac{\eta}{1-\eta}} (1-\eta)$$

In addition to earning profit, entrepreneurs must also choose how much to invest in their productivity which determines their occupational choice and value in the following period. Investments in productivity are costly and their outcome follows a binomial process, the expected value of which is chosen by entrepreneurs. The form of productivity adoption is similar to that in Buera and Fattal-Jaef (2018). In particular, agents hire labor so that with probability p, their productivity in the following period is upgraded from its current level z to $z\Delta$ where $\Delta > 1$. With probability $1-p$, productivity is downgraded symmetrically to $z\Delta^{-1}$. The labor cost required to ensure probability p is given by the following function:

$$i(p, z) = z\mu(e^{\phi_e p} - 1)$$

where $\mu > 0$ and $\phi_e > 1$ so that the labor required for investment is strictly increasing in z, as in Atkeson and Burstein (2010), and is convex in the probability of successful investment. Scaling by z ensures that Gibrat's law holds for large firms, that is, the growth rate is independent of firm size for large firms.

Notice, there are two sources of firm exit, the first is endogenous and due to downgrading from risky investments in productivity. The second is exogenous and due to idiosyncratic productivity shocks which occur with probability δ_e.

Having described the static maximization and investment problem, the value of an entrepreneur with productivity z is defined as follows:

$$V^e(z) = \max_p \quad \pi(z) - w \cdot i(p,z) + \beta(1-\delta_e)\left[pV(z\Delta) + (1-p)V(z\Delta^{-1})\right] + \beta\delta_e \int V(z')dF(z')$$

where $F(z)$ is an exogenous and time invariant distribution and $V(z)$ is the value of an agent with productivity z which is determined by comparing the value in entrepreneurship and the value in employment and defined below.

3.2 Worker's Problem

Workers earn wages and choose how much effort to exert in order to learn from their employers. Since workers contribute identically to production they earn the market wage w regardless of their own or their employer's productivity. On the other hand, learning is costly and depends on productivity of the worker (denoted here by x), the employer's productivity z and the worker's choice variable q - the probability of successfully learning from an employer. A worker's productivity in the following period, x', is given by:

$$x'(x,z) = \begin{cases} x + \theta(z-x) & \text{with probability } q \\ x & \text{with probability } 1-q \end{cases}$$

where $\theta \in [0,1]$ determines the degree to which a worker can close the productivity gap between themselves and their employer. For instance, when $\theta = 1$, the employee will exactly adopt the productivity of their employer in the following period with probability q, while $\theta = 0$ is equivalent to the model without learning. Intermediate values of θ will, in equilibrium, move workers towards the right of the productivity distribution, first as more productive workers, to eventually forming spinouts. This learning process implies that spinouts from larger, more productive employers will, on average, be larger than spinouts from less productive employers. Also, this form of learning ensures that tenure with an employer is (weakly) positively associated with spinout formation - as observed in the data.

Given this stochastic learning process, the time cost involved with learning is assumed to have the following functional form:

$$c(q, x, z) = \nu(z - x)^{\rho}(e^{\phi_w q} - 1)$$

where $\nu, \rho > 0$ and $\phi_w > 1$ so this cost is increasing in the difference between worker and employer productivity and convex in q. This assumption captures two key empirical findings on spinout entry. Namely, that i) spinouts are more likely to enter from small rather than large firms and ii) more able workers (as proxied by conditional income in the data) are more likely to form spinouts. This functional form can be interpreted as reflecting a lower "student-teacher" ratio in small/low productivity firms leading to more effective learning. Similarly, the learning process imposes an upper bound on the amount that an employee can learn from their employer - namely some fraction of the employer-employee productivity gap.

Then, the value $V^w(x; z)$ for a worker of productivity x who is employed by an employer z is given by:

$$\begin{aligned} V^w(x; z) = \max_q w - wc(q, x, z) + \beta(1 - \delta_w)\left[qV\left(x'(x, z)\right) + (1 - q)V(x)\right] \\ + \beta\delta_w \int V(z')dF(z') \end{aligned}$$

where δ_w is the probability with which workers receive idiosyncratic productivity shocks from the exogenous distribution $F(z)$.

In order to fully characterize the value in employment, the assignment of workers to entrepreneurs must be specified. Recall that entrepreneurs are indifferent between all workers as each employee contributes equally towards production. However, given the learning structure, workers may be willing to accept a lower wage in order for the opportunity to learn from a particular employer - implying incentives for sorting. I abstract from this possibility and impose uniform assignment between employees and employers. That is, workers are randomly allocated across employers and earn an identical wage w when employed regardless of their own or their employer's productivity.[20] This assumption allows us to abstract from sorting and focus only on the role of learning for which there is ample empirical evidence.

Under the simplifying assumption of random assignment and given the endogenous stationary productivity distribution $\Psi(z)$, the value in employment for an agent of productivity x is given by:

$$W(x) = \int V^w(x; z') \frac{l(z')}{\int l(s) d\Psi(s)} d\Psi(z')$$

Then, the value $V(z)$ of an agent of productivity z is simply:

$$V(z) = \max \{W(z), V^e(z)\}$$

and the occupational choice of agents $o(z)$ satisfies the following:

$$o(z) = \begin{cases} 0 & \text{if } W(z) \geq V^e(z) \\ 1 & \text{if } W(z) < V^e(z) \end{cases}$$

where z^* is the threshold productivity level such that $W(z^*) = V^e(z^*)$.

3.3 Equilibrium

I focus on the *stationary competitive equilibrium* which consists of an endogenous, stationary productivity distribution $\Psi(z)$, optimal policies $\{l(z), p(z), q(x, z), o(z)\}$and wage w such that:

1) *The labor market clears*

$$\int [l(z) + i(p(z), z)] \cdot o(z) \cdot d\Psi(z) = \int (1 - o(z)) \cdot d\Psi(z)$$

where $i(p(z), z)$ is the optimal level of workers hired by entrepreneur z for investment.

2) *Optimal policy rules are determined by the following first order conditions:*

$$l(z) = z \left(\frac{\eta}{w}\right)^{\frac{1}{1-\eta}}$$

[20] Theoretically, this can be generated by assuming asymmetric information such that workers cannot distinguish employer productivity.

$$wi_p(p,z) = \beta(1-\delta_e)\left[V(z\Delta) - V(z\Delta^{-1})\right]$$

$$wc_q(q,x,z) = \beta(1-\delta_w)\left[V(x+\theta(z-x)) - V(x)\right]$$

3) The stationary distribution $\Psi(z)$ is endogenously determined and is consistent with policy rules of agents and satisfies the following:

$$\begin{aligned}
\Psi_{t+1}(z) = \Psi_t(z) &- \delta_e\left(1-F(z)\right)\int o_t(x)d\Psi_t(x) - \delta_w\left(1-F(z)\right)\int\left(1-o_t(x)\right)d\Psi_t(x) \\
&-(1-\delta_e)\left[\int_{z\Delta^{-1}}^{z} o_t(x)p_t(x)d\Psi_t(x) - \int_{z}^{z\Delta} o_t(x)\left(1-p_t(x)\right)d\Psi_t(x)\right] \\
&-(1-\delta_w)\int\left[\int_{\frac{z-(1-\theta)x}{\theta}}^{\infty}\left(1-o_t(x)\right)q_t(x,k)\lambda_t(k)dk\right]d\Psi_t(x)
\end{aligned}$$

where $\lambda_t(k)$ is the probability that a worker is employed by an employer of productivity k:

$$\lambda_t(k) = o_t(k)\frac{l_t(k)}{\int l_t(x')d\Psi_t(x')}d\Psi_t(k)$$

4 Calibration

To be consistent with the data, one period in the model corresponds to a year. So, the discount rate β is set to match the 6% annual interest rate in Mexico. The exogenous productivity distribution $F(z)$ is assumed to follow a Pareto distribution with a lower bound of 1 and tail parameter γ which is calibrated. The parameter governing the degree of learning θ is assumed to be 0.25 for Mexico. This choice is motivated by the findings of Jarosch et al. (2019) who estimate that learning from older co-workers leads to a 35 to 15 % gain in earnings.[21] Finally, I assume that ϕ_w, the parameter governing the convexity of the learning cost with respect to probability of success q is 10. This leaves a total of nine parameters that are jointly calibrated to match key features of the Mexican data, see table 5.

[21] Jarosch et al. (2019) use administrative data from Germany. In this context, $\theta = 0.25$ implies that a worker employed by an employer that is twice as productive as them experiences a 25% increase in productivity upon learning.

Table 5: Parameters

Parameter	Value	Basis
		Pre-determined
β	0.94	Annual Interest Rate
θ	0.25	See text
ϕ_w	10	Buera and Fattal-Jaef (2018)
		Calibrated
Δ	1.11	SD of Empl. Growth
η	0.56	Top 1% Income Share
μ	3.9×10^{-3}	Empl. Age 20 relative to Age 5
ϕ_e	12	Share of Entrepreneurs
δ_e	0.20	Exit Rate in ENOE
ρ	1.40	Entrant/Incumbent Employment Ratio
ν	2.0×10^{-3}	Aggregate Spinout Rate
δ_w	0.06	Spinout Entry from Large Employers
γ	1.20	Top 5% Empl. Share

Notes: Data on spinout rate, share of workers, and exit rate is computed from the matched ENOE data. The exit rate is defined as the share of all entrepreneurs in year y that were no longer engaged in entrepreneurship in year $y+1$. The ratio of spinout size at ages 5 and 20 is from the ENAMIN data. Standard Deviation of employment growth in large firms is computed using the World Bank Enterprise Survey data. Income share of the top 1% is from Campos-Vazquez et al. (2015). The employment share of the top 5% of firms is from the 2014 Economic Census in Mexico as reported by INEGI.

The innovation step size in productivity, Δ, is chosen to match the standard deviation of employment growth in large firms in Mexico.[22] Data for this measure is derived using the World Bank Enterprise Survey for Mexico in 2006 and 2010. Focusing on firms that have at least 100 employees, I find the standard deviation of annualized employment growth rate to be 0.10.[23]

The parameter governing the span of control of entrepreneurs, η is calibrated to be 0.56 and is chosen to match the income share of the top 1% of earners in Mexico as reported by Campos-Vazquez et al. (2015) . The scalar on cost of innovation, μ determines the level of investment per firm and is chosen to match the average employment of spinouts of age 20 relative to those of age 5 as estimated from the ENAMIN data. The parameters ϕ_e is chosen to match the share of entrepreneurs. The probability of receiving an idiosyncratic productivity shock as an entrepreneur, δ_e is chosen to match the exit rate from self-employment as estimated from the ENOE.[24]

The learning cost function is calibrated to be convex in the gap between employer and employee productivity with an associated exponent of $\rho = 1.40$. This value is chosen to match the ratio of

[22] Recall that given the binomial nature of the innovation process and that Gibrat's law holds for large firms, the standard deviation in employment growth will map directly into the step size parameter Δ.

[23] The standard deviation is similar when choosing higher thresholds of employment. Notice, the standard deviation of employment growth in Mexico is lower than that for the U.S. (0.25) as estimated by Atkeson and Burstein (2010).

[24] This exit rate is not the same as that in section 2.3 which measures the exit rate only for new spinouts.

employment in incumbent firms relative to entering firms and is estimated as the average of the ratio in both the ENAMIN and the World Bank Enterprise Survey data. The scalar parameter on the learning cost function ν is chosen to match the aggregate spinout rate in Mexico. The parameter δ_w is chosen to match the share of spinouts from the largest firm size category (those with over 500 employees), respectively. The Pareto tail parameter of the exogenous distribution $F(z)$ is chosen to match the employment share of the top 5% of firms by firm size. Data for this measure is taken from the 2014 Economic Census in Mexico.

Table 6: Targeted Moments

Moment	Data	Model
SD of Empl. Growth	0.10	0.10
Top 1% Income Share	0.25	0.23
Empl. Age 20 relative to Age 5	1.20	1.26
Share of Entrepreneurs	0.20	0.21
Exit Rate in ENOE	0.26	0.26
Entrant/Incumbent Employment Ratio	0.21	0.25
Aggregate Spinout Rate	0.07	0.06
Spinout Entry from Large Employers	0.01	0.02
Top 5% Empl. Share	0.58	0.53

Table 6 reports the model's fit with the targeted moments while figure A.7 in the appendix compares the (untargeted) employment weighted firm size distribution implied by the model to that in the data. Overall, the model slightly overestimates the share of small firms as well as spinout entry from large employers but otherwise performs well in replicating the features of the Mexican economy.

5 Results

In this section, I describe the stationary equilibrium and the mechanisms underlying the results in the calibrated model. I also document that the model performs well in matching a number of untargeted features of the data.

Stationary Distribution Shown in figure 4, the stationary distribution features a threshold productivity level, z^* above (below) which agents are entrepreneurs (employees). There is a discontinuity at this threshold characterized by a large mass of high productivity marginal workers.

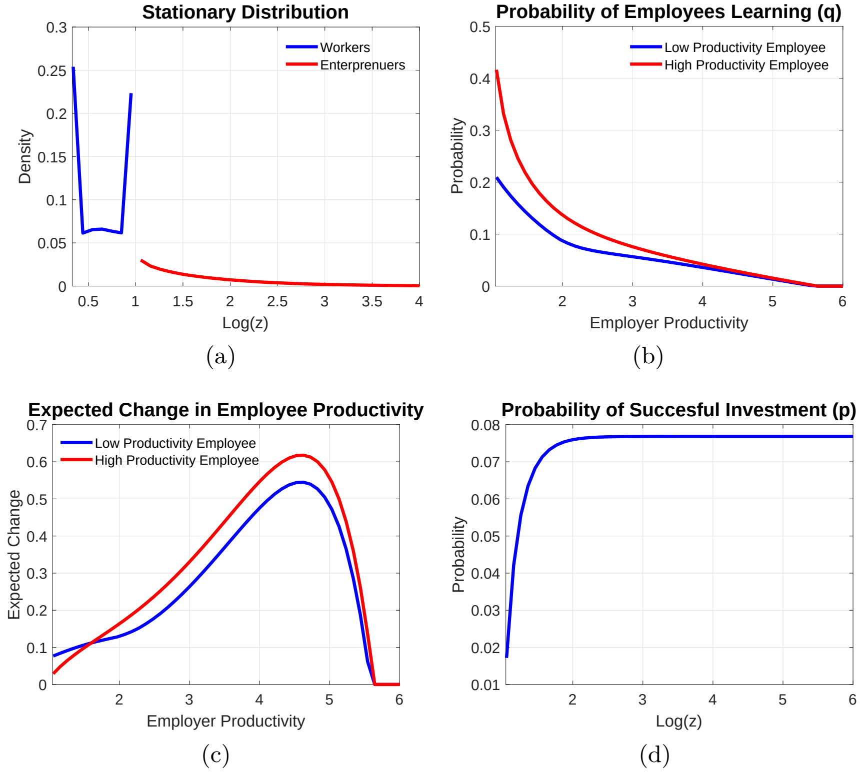


Figure 4: Stationary Equilibrium

Notes: Panel (a) plots the stationary distribution $\Psi(z)$. Panel (b) plots the optimal probability of learning $q(x;z)$ for both high and low productivity workers by employer productivity z. Panel (c) plots the expected gain in productivity from employee learning and is computed as $q(x;z)\theta(z-x)$. Panel (d) shows the optimal investment intensity in terms of the probability of successful investment by entrepreneurs, $p(z)$.

There are two forces driving this discontinuity: productivity downgrading of entrepreneurs and learning by employees. First, as investments of marginal entrepreneurs fail, they switch from being low productivity entrepreneurs to high productivity workers. Second, as employees learn from their employers, they move along the productivity distribution, initially becoming more productive workers before forming spinouts.[25]

Probability and Gains of Learning Panel (b) and (c) of figure 4 document the optimal probability and productivity gains from learning by employer productivity. There is a weakly negative relationship between the probability of learning and employer size for all workers with employees of very high productivity/large firms choosing not to learn.[26]When exerting effort, high productivity

[25]A version of the model which features only exogenous firm exit, that is with no downgrading, also leads to a discontinuity at the productivity threshold. However, depending on the nature of exogenous exit, there is not necessarily a bi-modailty in the distribution of workers.

[26]In this calibration, only around 1% of firms have high enough productivity such that the lowest productivity employees exert no effort in learning. Spinouts created from these firms are entirely due to idiosyncratic productivity

workers choose a higher probability of learning. The positive (negative) relationship between worker (employer) productivity and probability of learning can be understood by comparing the gains and costs from learning. In this calibration, both the cost and gains from learning are increasing in employer productivity. However, the gains from learning increase in a relatively less convex manner than the costs; hence, the optimal probability of learning declines in employer size.[27]Conversely, both the cost and gains from learning are decreasing in employee productivity - more productive workers have a higher likelihood of learning. As a result, spinout entry is higher for high ability employees as documented in the data.

The expected gains from learning, shown in panel (c), are non-monotonic in employer productivity - increasing with most employers and declining for only the most productive employers (as the probability of learning reaches 0). This relationship holds for all workers. However, when the employer-employee productivity gap is smallest, e.g. when the most productive workers are employed by the least productive firms, expected gains from learning are low.

Investment Intensity Panel (d) of figure 4 shows investment intensity by firm size (productivity). Larger firms invest at a higher rate than smaller firms.[28]This can be understood by considering the incentives for innovation for marginal entrepreneurs. Entrepreneurs close to the margin z^* face two forces which lower their incentive to innovate relative to more productive firms. First, they are more likely to receive an exogenous productivity shock (drawn from $F(z)$ with probability δ_e) that is higher than their current productivity relative to larger firms. Second, for small firms, failed investments might induce exit following which, agents will have the option to learn from their employer as workers in the following period(s). This option value of learning in employment is particularly valuable to entrepreneurs near the margin since their future employer is likely to be further from the margin than they were.[29] Both these forces drive down the incentives for innovation and result in the investment profile seen in panel (d). Hence, the optimal investment

draws of workers.

[27]The optimal learning probability q is such that $q \propto \log\left[\frac{V(\theta z+(1-\theta)x)-V(x)}{(z-x)^\rho}\right]$. Given that the value function $V(\cdot)$ is weakly convex, by Jensen's inequality, $\log\left[\frac{V(\theta z+(1-\theta)x)-V(x)}{(z-x)^\rho}\right] \leq \log\left[\frac{\theta(V(z)-V(x))}{(z-x)^\rho}\right]$. Then, a weakly negative relationship between employer productivity and learning probability requires the following to hold $V'(z) \leq \rho\frac{[V(z)-V(x)]}{(z-x)}$.

[28]Recall, that and due to the scaling of investment cost by productivity investment for the largest firms is constant.

[29]The trade off between investment and employee learning is also present in the framework developed by Baslandze (2017).

probability $p(z)$ is weakly increasing in productivity. A consequence of this is that spinouts which start small are less likely to grow than spinouts that start large.

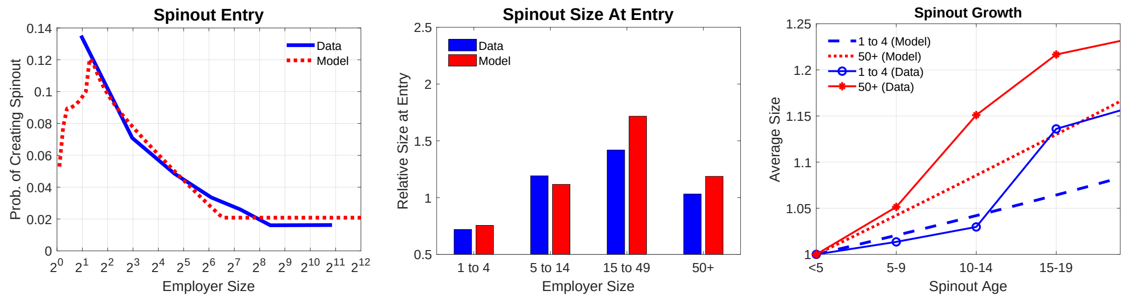
Having discussed the stationary equilibrium and the underlying mechanisms, I now compare untargeted features of the data with their model implied counterparts..

Spinout Entry Panel (a) of figure 5 plots the spinout entry rate in the model and data. For very small firms, those with fewer than 2 employees, the model predicts a positive relationship between spinout entry and employer size. Since the data only provides bins of employer size, I cannot verify if this pattern is also observed in the data for very small firms. In the model, this positive relationship is due to the learning process which is such that only a subset of workers in small firms obtain productivity levels above z^* following learning. For example, consider the set of employees $x \in [1, z^*)$ employed by a low productivity entrepreneur $z^* + \epsilon$. Only the subset, $x \in [z^* - \epsilon\frac{\theta}{1-\theta}, z^*)$ are able to form spinouts. As employers (that is, ϵ) grow larger, more workers create spinouts after learning, leading to the initial positive relationship in firms size and spinout entry.[30]For all other employers, the model fits well the observed negative relationship between the likelihood of spinout entry and employer size. The exogenous productivity shocks δ_w are the only source of spinout entry for workers from very large employers and is hence constant.[31]

Spinout Size The model qualitatively matches the positive relationship between employer size and spinout size at entry as shown in panel (b) of figure 5. The figure plots the observed and model implied average initial size of new spinouts (normalized by the average size of all spinouts). Conditional on learning, employees of larger employers learn relatively more. Hence, the spinouts that they form are, on average, larger. However, as emphasized above, employees in the largest firms find it too costly to learn from their employers and hence spinouts from this set of firms are more likely to be spawned via exogenous productivity shocks - which are, on average, smaller. This leads to the average initial size of spinouts from large (50+) employers to be lower in the model

[30]Notice, that unless $\theta = 1$, that is when employees exactly adopt their employer's productivity, there will always be a subset of workers who are unable to form spinouts when working for the smallest firms.

[31]In this calibration, less than 2% of workers form spinouts due to idiosyncratic productivity draws.



(a) (b) (c)

Figure 5: Data Comparison with Model

Notes: Panel (a) plots the model implied spinout entry rate for employers with at least 1 employee along with the entry rate observed in the matched ENOE sample. Panel (b) plots the average wage bill for spinouts that are fewer than 5 years of age by employer size as observed in the 2012 ENAMIN sample. The model counterpart plots the average productivity of spinouts at entry by employer size. Recall, that in the model, spinout wage bill is proportional to productivity. Both data and model measures of average size are scaled by average spinout size for all spinouts. Panel (c) plots, on the right axis with solid lines, average spinout size by age as observed in the data for spinouts from small and large employers. On the left axis, with dashed lines, panel (c) plots the average size of spinouts conditional on growing by age. Both measures are normalized to 1 at entry.

than the average initial size of spinouts from medium (15 to 49) sized employers. This pattern is also observed in the data, although the difference is not statistically significant (see table 3). Quantitatively, the model slightly over (under) predicts the size of spinouts from large (small) employers.

Panel (c) qualitatively compares the model's implications to that in the data by plotting the life cycle profile of spinouts conditional on growth (i.e. with no downgrading). Since spinouts from large employers are larger at entry, they invest more in productivity and hence are more likely to grow than spinouts from smaller firms. This results in a steeper age-size profile for spinouts from large employers - as observed in the data. It also implies that spinouts from small employers are more likely to exit than those from large employers as found in the data.

Overall, the calibrated version of the model matches both the negative relationship between employer size and spinout entry and the positive relationship between spinout performance and employer size.

6 Quantitative Analysis

In this section, I conduct two quantitative exercises that highlight the importance of the relationship between employer size and spinout dynamics. The first exercise investigates the factors that drive differences in aggregate spinout formation between U.S. and Mexico and asks whether these factors

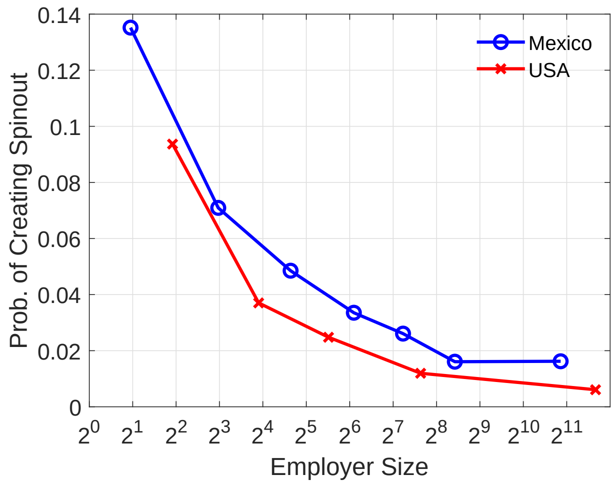


Figure 6: Spinout Entry, US and Mexico

Notes: Data from Mexico is from the matched ENOE sample covering 2005Q1 to 2016Q3. Data from the US is from the matched IPUMS March CPS covering 1997 to 2015. Both samples include only full-time, male, non-agricultural employees aged between 18 and 65. Details are in the appendix. The vertical axis shows the share of employees that transitioned to entrepreneurship over a year without any intervening spells of non-employment. The horizontal axis reports the average firm size for each firm size bin. The five firm size bins for the US are: Under 10, 10 to 49, 50 to 99, 100 to 499 and 500+ employees and average for each bin is computed by assuming that the firm size distribution follows a Pareto distribution with tail parameter 1.05 as in Axtell (2001). For details on the Mexican data see figure 2.

account for cross-country variation in other outcomes. The second exercise studies the benchmark model economy's response to a temporary subsidy given to small firms and compares the response to one from a simpler environment with no learning and hence exogenous spinout formation.

6.1 Cross-Country Differences

Figure 6 shows that employees in the U.S. are less likely to form spinouts relative to Mexico across all firm size categories. While the gap is small, taken together with the differences in firm size distribution between the two economies, the aggregate spinout entry rate in Mexico is more than three times the rate observed in the U.S. (6.9% and 2.1%). Beyond the aggregate spinout entry rate, table 7 summarizes a number of other differences that are observed between these two economies.

While the U.S. and Mexican economies differ along a number of important dimensions, I focus on two: learning efficiency and investment cost.[32] I first test whether differences in learning efficiency, captured by θ, can reconcile the observed variation in spinout entry rates and I find that it cannot. Next, I test whether the probability of investment, modeled here as a shift in the scalar parameter

[32]Notice, the model is invariant to changes in aggregate productivity which effect all entrepreneurs. Since investment and learning cost is in units of labor, change in productivity act to simply adjust wages and leaves allocations unchanged.

Table 7: Data Summary, USA and Mexico

	Mexico	US	Ratio
Aggregate Spinout Rate	0.069	0.021	0.33
Output per worker (thousands, 2010USD)	38	112	2.95
Avg. Firm Size (Age 16-20)/(Age<5)	1.20	2.22	1.87
Average Firm Size	5.7	21.8	3.82
Share of Entrepreneurs	0.19	0.09	0.44

Notes: Aggregate spinout rate is the share of employees in year y that form spinouts in the following year as computed from the ENOE and CPS. Output per worker is computed using the Penn World Table (PWT 9.0) data for 2014. Average firm size by age for the U.S. comes from the Business Dynamics Statistics Database in 2014. The average firm size for Mexico is computed assuming that the firm size distribution follows a Pareto distribution with tail parameter 1.24. This tail parameter is estimated using data from the 2006 and 2010 World Bank Enterprise Surveys for Mexico and the method detailed in Axtell (2001). The share of entrepreneurs is computed from the ENOE and CPS for Mexico and U.S. respectively.

on investment cost μ, can explain spinout entry rates and find that it too cannot. Finally, by letting both learning and investment parameters vary, I show that these two factors can jointly account for variation in spinout entry rates as well as the other outcomes in table 7. I describe these results in detail below.

Learning Efficiency Since this paper's focus is on employee learning and our aim in this section is to identify the mechanisms leading to lower spinout entry in the U.S., a natural candidate for driving cross-country variation is the learning efficiency parameter θ.[33] Changes in this parameter will have a direct effect on incentives to learn and hence the probability of spinout formation. However, the interpretation of θ requires clarification.[34] Since changes in θ act to scale the productivity gain from learning, I interpret it as capturing a form of aggregate managerial quality in the economy. In particular, it could represent those managerial practices that pertain to the review and development of employees through performance monitoring.[35]

Given this interpretation, cross country evidence on management practices indicates that average managerial quality is higher in the U.S. relative to Mexico (see for example Bloom and Van Reenen (2007) and the World Management Survey). This should be modeled by a *higher* value of θ. That

[33]Notice, spinout entry rates are not identified separately from the learning efficiency parameter θ and the learning cost parameter ν. I implicitly model a lower cost of learning by increasing θ.

[34]A simple interpretation of θ is that it reflects differing degrees of educational attainment across economies.

[35]These management practices are distinct from those that directly impact firm performance such as the the adoption of modern production techniques or standardization of processes. Practices that impact improve the possibility of employee learning can be identified in the World Management Survey (WMS) available at http://worldmanagementsurvey.org/. This survey measures cross-country differences in management quality and of particular relevance here are the measures of performance monitoring and talent management, which are interpreted as captured in θ. These practices are measured by asking questions such as: *What kind of Key Performance Indicators (KPIs) would you use for performance tracking? How do you review your KPIs?* and *If you had a worker who could not do his job what would you do?* On the other hand operations management is measured by asking about

is, for the same effort, employees learn more from their employers. It might seem counter-intuitive that making it *easier* to learn leads to *lower* spinout rates but this is exactly the outcome in the model and can be understood by noting the general equilibrium response from increasing θ.

Making employee learning cheaper increases the value in employment. This in turn, shifts the occupational choice of agents so that the equilibrium productivity threshold, z^*, shifts to the right. Now, only the most productive agents pursue entrepreneurship. So, while it is easier to learn from an employer as θ increases, workers will also be employed by more productive employers. This in turn, makes it costlier for workers, particularly low productivity workers to learn. The improvement in learning efficiency is offset by the increase in learning cost due to changes in the occupational choice of agents. As a result, overall spinout entry declines.

Table 8: Results relative to Benchmark Model

	Data	Model (relative to benchmark)		
	U.S. rel. to Mexico	$\theta = 1$	$\mu = 5.4 \times 10^{-7}$	$\theta = 0.78$, $\mu = 3.3 \times 10^{-7}$
Aggregate Spinout Rate	0.33	0.73	0.53	0.33*
		[40%]	[69%]	[100%]
Firm Growth	1.87	0.97	1.87*	1.87*
		[-3%]	[100%]	[100%]
Output per worker	2.95	2.17	1.29	2.81
		[60%]	[15%]	[93%]
Average Firm Size	3.82	1.48	1.23	2.54
		[17%]	[8%]	[55%]
Share of Entrepreneurs	0.44	0.72	0.84	0.45
		[49%]	[28%]	[98%]

Notes: The first column of the table shows the observed ratio of U.S. measures to those in Mexico. The remaining columns show the model implied ratios as relative to the benchmark calibration. Percentages in brackets report the share of cross-coountry variation. * indicates those parameters that were targeted.

Table 8 reflects this intuition by showing the results when increasing θ from 0.25, as in the benchmark, to the maximal value 1.[36] Reported in the first column, increasing θ leads to a decrease in the share of entrepreneurs and increases in both output per worker and the average firm size – accounting for a significant portion of observed cross-country differences. However, despite the high learning efficiency, the model can only account for 40% of the observed cross-country variation in spinout rates. Further, by increasing θ, entrepreneurs have lower incentives to innovate and this leads to a slight *decrease* in firm growth over the life cycle. Given this counterfactual result on firm growth as well as the inability of θ alone to account for spinout entry, I test whether the cost of

[36] Recall that I impose $\theta \in [0, 1]$. The model requires $\theta > 1$ when calibrating the model to exactly match the U.S. aggregate spinout rate.

investment is sufficient for explaining spinout entry.

Cost of Investment Differences in firm growth across countries have been well documented in the literature (see for example Hsieh and Klenow (2014) and Eslava et al. (2019)). Explanations for slower firm growth in developing economies have centered around institutional differences which lead to differences in the incentives and probability of successful investment (see for example Akcigit et al. (2016) and Caunedo and Yurdagul (2018)). I embed these ideas in the model by varying the cost of investment. In particular, I lower the scalar parameter on the investment cost function μ to exactly match firm higher growth rate in the U.S. and study the extent to which this also explains variation in spinout entry. Intuitively, varying μ impacts spinout formation in a manner that is similar to varying θ. Increasing the incentives for innovation leads to an increase in investment intensity which in turn increases the demand for labor employed for investment purposes. This increases the value of employment and pushes the threshold z^* above which agents become entrepreneurs to the right. As with increasing θ, the shift in the productivity threshold increases the average productivity of employers, making it costlier to learn from them, hence lowering spinout rates.

The third column of table 8 shows the results from re-calibrating μ: lower cost of investment accounts for a significant share of variation in spinout formation - 69%. However, it fails to fully account for the U.S. - Mexico difference. Further, lowering investment costs explains relatively little of the cross-country variation in output per worker, average firm size and the share of entrepreneurs. So, while differences in the cost of investment are important in this model which includes spinouts, it alone cannot account for the gap in spinout formation rates between the two economies studied here.

Finally, the last column of table 8 shows the results from jointly re-calibrating both θ and μ to match spinout entry and firm growth in the U.S. respectively. By varying both these parameters, the model can account for almost all of the observed difference in output per worker and the share of entrepreneurs, along with 55% of the variation in average firm size. These results highlight the importance of considering factors that impact spinout formation in order to understand aggregate

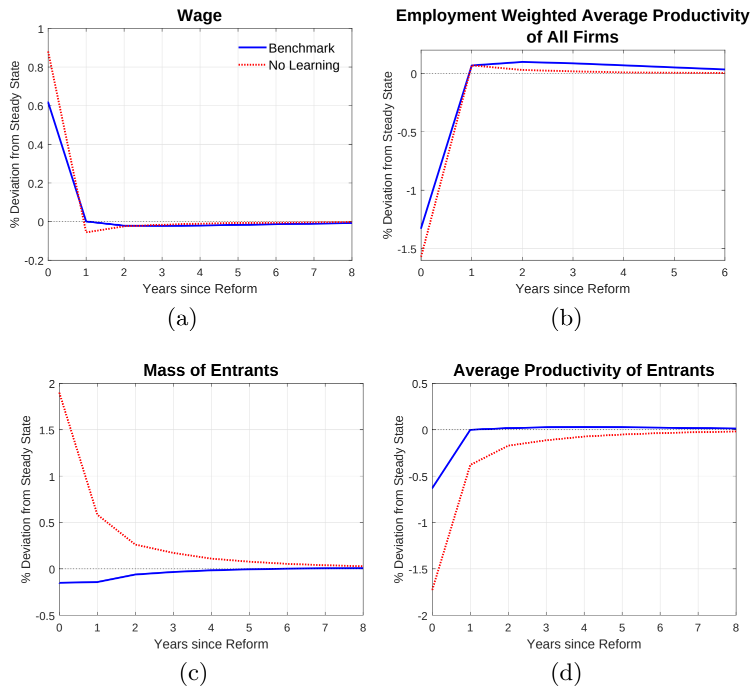


Figure 7: Transitional Dynamics Following a Subsidy to Small Firms

Notes: Each of the panel plots the percent deviation from steady state values in the benchmark model (solid line) and the model without learning (dashed line) to a one period subsidy to small firms. Panel (a) plots the response of wages, panel (b) plots the employment weighted average productivity of all firms. Panels (c) and (d) plot the mass and average productivity of entrants, respectively.

outcomes across economies.

6.2 Policy Implications

In this section, I study the model economy's response to a temporary subsidy given to small firms. To understand the policy implications of endogenizing the link between existing firms and new spinouts, I compare the benchmark model to a version where there is no learning. That is, all new entrants are determined exogenously.

I construct the "no learning" model by setting θ to be 0 and re-calibrating all remaining parameters to match moments in the data.[37] In this version of the model, the worker's problem is much simpler and the value in employment is given by:

$$W(z) = w + \beta\left(1 - \delta_w\right) V(z) + \beta \delta_w \int V(z') dF(z')$$

[37]Parameter values are reported in appendix B.

where δ_w and $F(\cdot)$ are the only (exogenous) source of spinouts and the spinout rate is given by $\delta_w\,(1 - F(z^*))$.

The temporary reform is a one period 3% subsidy on output given to firms that hire fewer than 5 employees. This policy is similar to those enacted by, for example, Fondo PyME in Mexico or the Small Business Administration in the U.S. On impact, at time t, the value in entrepreneurship (in both the benchmark and "no learning" economy) is:

$$
\begin{aligned}
V_t(z) = \max_{p_t, l_t} (1+\tau_{\bar{z}}) z^{(1-\eta)} l_t^{\eta} - w_t l_t - w_t i(p,z) + \beta(1-\delta_e)\left[p V_{t+1}(z\Delta) + (1-p) V_{t+1}(z\Delta^{-1})\right] \\
+ \beta\delta_e \int V_{t+1}(z') dF(z')
\end{aligned}
$$

where $\tau_{\bar{z}}$ is equal to 3% for entrepreneurs with productivity such that they employ less than 5 employees (as computed in the stationary equilibrium) and 0 otherwise. Notice, that this policy distorts labor allocations and directs employment towards less productive, smaller firms.

Figure 7 compares the perfect foresight transition dynamics of wages, average firm productivity and characteristics of entrants following the subsidy.

Focusing first on wages in panel (a), both economies feature a qualitatively similar response; wages initially rise as labor demand increases and then fall before slowly transitioning back to steady state values. The benchmark economy features a more muted response with a longer transition. When employees can learn, reallocating labor towards smaller firms endogenously increases the value in employment. This is due to the cheaper learning opportunities in smaller firms. The gain from the re-shuffling of employment is greatest for low ability workers who have the the largest employer-employee productivity gap thus have the most to learn from small firms. The endogenous change in the value of employment implies that, for the same policy response, wages must change by a smaller amount to clear the labor market in the benchmark economy.

Panel (b) plots the employment weighted average productivity of firms. On impact, average productivity declines in both models. Along the transition, average productivity increases above steady state values before equilibrating back to its stationary levels. Differences in the speed and magnitude of the transition are driven by the differences in entry dynamics shown in panels (c) and (d).

First, panel (c) reports the mass of entrants.[38] In the model without learning, the mass of entrants increases on impact and then slowly returns to its steady state values. The increase and recovery is entirely driven by changes in the productivity threshold, z^*, above which agents become entrepreneurs. Recall, in the "no learning" framework, a share $\delta_w\,(1 - F(z_t^*))$ of workers will form new firms. Although, the dynamics of the productivity threshold z^* in both models are similar, when firm entry is endogenous, the mass of entrants *declines* on impact before returning to its steady state values. This stark difference is due, once again, to the labor reallocation effect. Many workers that were preciously employed in large firms are now employed for smaller firms. This limits the amount that they can learn from their employer and many workers who may previously have learned from their (larger) employer to form spinouts are now unable to learn enough; lowering the mass of entrants.

Despite not gaining enough productivity to form spinouts, overall learning is cheaper and increases with workers moving towards the right of the productivity distribution. This increased learning following the subsidy has long-lasting implications and results in *higher* quality entrants along the transition path in the benchmark economy; shown in panel (d). Indeed, the (unweighted) average productivity of entrants in the benchmark model reflects the productivity of firms that employees are working for. This contrasts with the quality of entrants in the "no-learning" model which monotonically returns back to its steady state values following an initial decline driven solely by changes in the productivity threshold.

This simple exercise highlights the importance of incorporating the relationship between employer size and spinout dynamics when designing policies targeting existing firms.[39] As shown above, such policies will have long-lasting and meaningful implications for future firm entry.

[38] The dynamics of the spinout rate, i.e. the mass of entrants divided by the mass of workers are qualitatively similar.

[39] Alternative policies which impact new firm entry such as a temporary change in entry costs, yields qualitatively similar results: the model with learning features longer transitions and differing dynamics of new entrants compared to the model without learning.

7 Conclusion

This paper studied the relationship between characteristics of existing firms and the entry and post-entry dynamics of spinouts. In particular, I document the relationship between employer size and spinout dynamics and use a theoretical model to show that this relationship is important for macroeconomic outcomes. Using detailed micro-data from Mexico, I find a negative relationship between employer size and spinout entry, and a positive relationship between employer size and spinout size and growth. Novel to the literature on spinouts is the finding that employer size is related to spinout size, not only at entry but also over the life cycle – up to 20 years after entry.

To establish the importance of the link between employer size and spinout dynamics, I developed a model of occupational choice in which employees learn from their employers and form spinouts, with larger firms spawning larger spinouts that are more likely to grow. The calibrated version of the model reconciles the empirical evidence and is then used to test the importance of the connection between existing firms and new firms by conducting two quantitative exercises. The first exercise investigates the factors that lead to lower spinout entry rates in U.S. relative to Mexico. Through the lens of the model, I tested two factors which might explain these differences; i) the cost of investment and ii) the efficiency with which employees learn from employers. I found that differences in either factor on its own cannot account for cross-country differences in spinout formation, However, jointly these two factors can fully account for not only spinout formation but also cross-country variation in output per worker and 55% of the variation in average firm size. The second quantitative exercise highlights how employee learning, which drives the relationship between employer size and spinout dynamics, influences an economy's response to policies affecting existing firms. By comparing the benchmark model to a model without learning, I evaluated the response to a temporary subsidy given to small firms. The two models featured starkly different implications to the same policy. The model with learning not only features longer transitions, but the productivity of new entrants reflects characteristics of existing firms which is not the case for the model without learning.

Overall, this paper establishes and emphasizes the importance of the relationship between existing firms and new firms. While I focused on employee learning to drive this relationship, I abstracted from issues of selection and sorting. An exciting avenue for future research would be to not only incorporate both learning and selection but also to study the importance of factors that impact selection, such as labor market frictions, in influencing spinouts and aggregate outcomes.

References

Abebe, G., M. Fafchamps, M. Koelle, and S. Quinn (2019): "Learning Management Through Matching: A Field Experiment Using Mechanism Design," Working Paper 26035, National Bureau of Economic Research.

Akcigit, U., H. Alp, and M. Peters (2016): "Lack of Selection and Limits to Delegation: Firm Dynamics in Developing Countries," Working Paper 21905, National Bureau of Economic Research.

Andersson, M. and S. Klepper (2013): "Characteristics and performance of new firms and spinoffs in Sweden," *Industrial and corporate change*, 22, 245–280.

Asturias, J., S. Hur, T. J. Kehoe, and K. J. Ruhl (2019): "Firm Entry and Exit and Aggregate Growth," Tech. rep., Federal Reserve Bank of Cleveland, Working Paper 19-03.

Atkeson, A. and A. T. Burstein (2010): "Innovation, firm dynamics, and international trade," *Journal of political economy*, 118, 433–484.

Axtell, R. L. (2001): "Zipf distribution of US firm sizes," *Science*, 293, 1818–1820.

Baslandze, S. (2017): "Spinout Entry, Innovation, and Growth," *Working Paper*.

Berglann, H., E. R. Moen, K. Røed, and J. F. Skogstrøm (2011): "Entrepreneurship: Origins and returns," *Labour economics*, 18, 180–193.

Bloom, N., B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts (2013): "Does management matter? Evidence from India," *The Quarterly Journal of Economics*, 128, 1–51.

Bloom, N. and J. Van Reenen (2007): "Measuring and explaining management practices across firms and countries," *The Quarterly Journal of Economics*, 122, 1351–1408.

Brooks, W., K. Donovan, and T. R. Johnson (2016): "Learning Managerial Skills: Evidence from Kenyan Microenterprises," Tech. rep., Working Paper.

Bruhn, M., D. Karlan, and A. Schoar (2018): "The impact of consulting services on small and medium enterprises: Evidence from a randomized trial in mexico," *Journal of Political Economy*, 126, 635–687.

Buera, F. J. and R. N. Fattal-Jaef (2018): *The dynamics of development: Innovation and reallocation*, The World Bank.

Campos-Vazquez, R., E. Chávez, and G. Esquivel (2015): "A New Approach for Top Income Shares: Mexico Since the 1990's," .

Caunedo, J. and E. Yurdagul (2018): "Who Quits Next? Firm Growth in Growing Economies," *Economic Inquiry*.

Chari, V. V. and H. Hopenhayn (1991): "Vintage human capital, growth, and the diffusion of new technology," *Journal of political Economy*, 99, 1142–1165.

Clementi, G. L. and B. Palazzo (2016): "Entry, exit, firm dynamics, and aggregate fluctuations," *American Economic Journal: Macroeconomics*, 8, 1–41.

Colonnelli, E., J. Tåg, M. Webb, and S. Wolter (2018): "A Cross-Country Comparison of Dynamics in the Large Firm Wage Premium," in *AEA Papers and Proceedings*, vol. 108, 323–27.

Dasgupta, K. (2012): "Learning and knowledge diffusion in a global economy," *Journal of International Economics*, 87, 323–336.

Donovan, K., J. Lu, and T. Schoellman (2018): "Labor Market Flows and Development," .

Elfenbein, D. W., B. H. Hamilton, and T. R. Zenger (2010): "The small firm effect and the entrepreneurial spawning of scientists and engineers," *Management Science*, 56, 659–681.

Eslava, M., J. C. Haltiwanger, and A. Pinzon (2019): "Job creation in Colombia vs the U.S.: up or out dynamics meets the life cycle of plants." Working Paper 25550, National Bureau of Economic Research.

Fajnzylber, P., W. Maloney, and G. M. Rojas (2006): "Microenterprise dynamics in developing countries: How similar are they to those in the industrialized world? Evidence from Mexico," *The World Bank Economic Review*, 20, 389–419.

Foster, L., J. Haltiwanger, and C. Syverson (2008): "Reallocation, firm turnover, and efficiency: selection on productivity or profitability?" *American Economic Review*, 98, 394–425.

Foster, L., J. C. Haltiwanger, and C. J. Krizan (2001): "Aggregate productivity growth: lessons from microeconomic evidence," in *New developments in productivity analysis*, University of Chicago Press, 303–372.

Franco, A. M. and D. Filson (2006): "Spin-outs: knowledge diffusion through employee mobility," *The RAND Journal of Economics*, 37, 841–860.

Haltiwanger, J., R. S. Jarmin, and J. Miranda (2013): "Who creates jobs? Small versus large versus young," *Review of Economics and Statistics*, 95, 347–361.

Hsieh, C.-T. and P. J. Klenow (2014): " The Life Cycle of Plants in India and Mexico," *The Quarterly Journal of Economics*, 129, 1035–1084.

Hsieh, C.-T. and B. A. Olken (2014): "The missing "missing middle"," *The Journal of Economic Perspectives*, 28, 89–108.

Hurst, E. G. and B. W. Pugsley (2015): "Wealth, tastes, and entrepreneurial choice," Tech. rep., National Bureau of Economic Research.

Jarosch, G., E. Oberfield, and E. Rossi-Hansberg (2019): "Learning from Coworkers," Tech. rep., National Bureau of Economic Research.

Jovanovic, B. (2014): "Misallocation and growth," *American Economic Review*, 104, 1149–71.

Leung, D., C. Meh, and Y. Terajima (2008): "Firm size and productivity," Tech. rep., Bank of Canada Working Paper.

Lucas, R. E. (1978): "On the size distribution of business firms," *The Bell Journal of Economics*, 508–523.

Lucas, R. E. and B. Moll (2014): "Knowledge growth and the allocation of time," *Journal of Political Economy*, 122, 1–51.

Muendler, M.-A., J. E. Rauch, and O. Tocoian (2012): "Employee spinoffs and other entrants: Stylized facts from Brazil," *International Journal of Industrial Organization*, 30, 447–458.

Poschke, M. (2013): "'Entrepreneurs out of necessity': a snapshot," *Applied Economics Letters*, 20, 658–663.

Pugsley, B. W., P. Sedlacek, and V. Sterk (2019): "The Nature of Firm Growth," *Working Paper*.

Roys, N. and A. Seshadri (2014): "Economic development and the organization of production," *Working Paper*.

Sørensen, J. B. and D. J. Phillips (2011): "Competence and commitment: employer size and entrepreneurial endurance," *Industrial and Corporate Change*, 20, 1277–1304.

A Data Appendix

A.1 Identifying Spinouts

ENOE Spinouts are identified in the ENOE as those respondents that transition from employment to entrepreneurship. I begin by first restricting the sample to include only male respondents between the ages of 18 and 65 who are engaged in economic activity in the private, non-agricultural sector, earn at least the minimum wage in employment and report non-negative earnings as entrepreneurs. It is worth noting that the exclusion of female respondents is motivated by differences in the sources of new female entrepreneurs observed in the data. Figure A.1 shows that

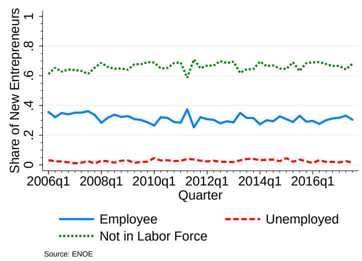


Figure A.1: Annual transitions rate for new female entrepreneurs

Notes: The sample uses data from the matched ENOE sample covering 2005Q1 to 2016Q3 and includes only those aged between 18 and 65. The vertical axis shows the share of entrepreneurs in year $y + 1$ by their occupation status in year y.

most new female entrepreneurs come from out of the labor force, in stark contrast to the source of most new male entrepreneurs who come from employment. Since these differences are not explained by differences in labor force participation, I include only male respondents in the empirical analysis.

Information in the ENOE allows us to ensure that transitions from non-employment to entrepreneurship are not characterized as spinouts. In particular, I only consider those employees who voluntarily quit their previous place of employment as being eligible for forming spinouts. There are two questions in the ENOE that allows us to identify this group of former employees. Respondents are asked why they left their previous place of employment. If individuals report as having quit, a follow up question asks the primary reason for doing so.[40] I include only those individual who report one of the following as being their primary reason for quitting i) *wanted to earn more income*, ii) *wanted independence*, iii) *lack of opportunities to excel*. Other reasons include *being forced to resign*, *harassment*, *conflict with superior*, *marriage* and *changes in work conditions*. Taken together, these restrictions ensure that former employees are motivated by opportunity, rather than necessity, when they form their own enterprises. This is an important distinction since existing work, for example Poschke (2013), has shown significant differences in firm size and growth between these two groups of entrepreneurs.

Notice, that both the self-employed and employers are identified as spinouts when I study spinout entry in the ENOE data.[41] Table A.1 shows that identifying only employee to *employer* transitions as spinout entry also results in a negative relationship between prior firm size and spinout entry.

Exit in the ENOE is identified using a sample which is matched at the quarterly frequency. In particular, to measure exit I consider only those employees that transition from employment to self-employment between their first interview in quarter q and the next quarter $q + 1$ and remain self-employed up to quarter $q + 2$. From this sample, I then compute the exit rate as the share these new spinouts that are no longer self-employed in quarter $q + 5$, their last appearance in the ENOE. In this way, I aim to look at exit among only those spinouts that are relatively long-lived (i.e. at least two quarters).

I also consider spinout rates across industries and occupations in figure A.2. The figures shows that while the negative relationship in employer size and and spinout hold for all industries and occupations, there are striking

[40] See, for example, in the 2012 ENOE questions 9a and 9d.

[41] This is reasonable since most new entrepreneurs do not hire workers at entry. In the ENOE data 59% of all spinouts are self-employed.

Table A.1: Marginal Effects of Employer Size and Probability of Entry as Spinout with Employees

	(1) P_i	(2) P_i	(3) P_i
Employer Size ($D_{i,j}$)			
▷ 1 to 4	0.038***	0.042***	0.045***
	(0.002)	(0.002)	(0.004)
▷ 5 to 9	0.023***	0.024***	0.025***
	(0.002)	(0.002)	(0.004)
▷ 10 to 14	0.011***	0.012***	0.012***
	(0.002)	(0.002)	(0.004)
▷ 15 to 49	0.008***	0.008***	0.012***
	(0.001)	(0.001)	(0.003)
Log Income (y_i)	-	0.015***	0.017***
	-	(0.001)	(0.003)
Tenure in years (h_i)	-	-	0.001***
	-	-	(0.000)
Individual Controls	Y	Y	Y
Industry, State, Year Controls	Y	Y	Y
Pseudo R^2	0.092	0.098	0.106
N	190,608	190,450	50,564

Notes: The omitted variable for employer size is the dummy for those employers with at least 50 employees. All probit regressions control for industry, year, and state fixed effects. Controls for informality status of previous employer as well as demographics are also included. The demographic controls include a quadratic in total years of experience and education bins which correspond to those with less than a HS degree, those with a HS degree, those with at least a college degree, and those with at least a HS but no college degree. I also include an indicator variable for those in managerial occupations. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

differences in the level and slope of this relationship. Focusing first on industry spinouts, the figure shows that the spinout rate is highest for construction and high skill services. All other industries exhibit a much lower spinout rate, particularly, from small employers. The evidence on occupation shows that higher skill occupations such as managers and professional have much higher spinout rates than those from lower skilled occupations.

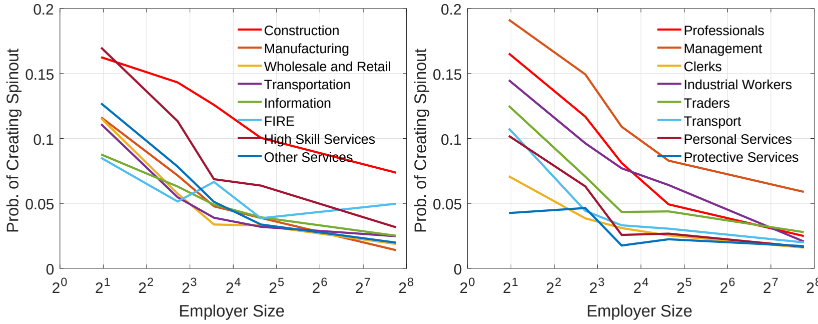
Next, I test whether differences in employee separations from employment by employer size may be driving the observed negative relationship between employer size and entry. Indeed, as highlighted by Donovan et al. (2018) employee separations are more prevalent in small rather than large firms. While the sample excludes individuals who experience unemployment or involuntary separations I test this in the full sample by studying transitions of all employees in year t to year $t+1$ by prior employer size. Table A.2 shows the transitions matrix. Consistent with Donovan et al. (2018) I find that that separations are negatively associated with employer size. However, as shown in the last column of table A.2, conditional on separating, former employees of smaller firms are almost twice as likely to enter entrepreneurship relative to those from the largest firms. This finding indicates that separations alone cannot fully explain the negative relationship between employer size and spinout entry.

Table A.2: Transitions of Employees from year y to year $y+1$ by Prior Employer Size

Employer Size:	(1) Employees	(2) Entrepreneurs	(3) Unemployment	(4) NILF	$\frac{(2)}{(2)+(3)+(4)}$
▷ 1 to 4	75.30	13.94	4.46	6.30	56.44
▷ 5 to 9	82.79	8.72	3.78	4.72	50.64
▷ 10 to 14	86.23	5.88	3.57	4.32	42.70
▷ 15 to 49	87.56	5.10	3.62	3.73	40.96
▷ 50+	91.03	2.77	3.17	3.03	30.88

Notes: The table report the share (in percentage) of employees that that either i) remain employed, ii) become entrepreneurs, iii) become unemployed or iv) go out of the labor force (NILF - Not In Labor Force). The sum of rows (1) through (4) should add up to 100. The fifth column shows the ratio of the value in column (2) and the sum of columns (2), (3) and (4).

ENAMIN Identification of spinouts in the ENAMIN sample relies on information about the work history of firm owners. Only those firms whose owners were employed in the quarter prior to starting their enterprise are identified



(a) Industry (b) Occupation

Figure A.2: Spinout Entry by Industry and Occupation

Notes: Data is from the matched ENOE sample covering 2005Q1-2016Q3 with sample restrictions described in appendix A. Industry groups are based on two-digit NAICS codes. High Skill Services includes health, education and management support services. FIRE includes finance, insurance and real estate while other services includes recreation, food, accommodation and all other non-governmental services. Occupation groups are based on the SOC classification codes in the ENOE.

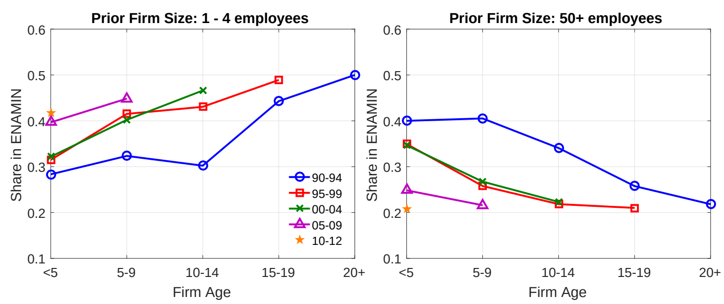


Figure A.3: Share of ENAMIN Sample by Cohort and Employer Size

Notes: Data is from the ENAMIN sample covering information from 1992 to 2012 .

as spinouts. Firms that were founded by multiple founders are excluded along with those owners who report having taken over a family firm. In addition to these restrictions, the ENAMIN data reports the primary reason why a firm owner left their previous place of employment and the primary reason for starting their enterprise. This information allows us to be consistent with the ENOE sample. I include, whenever available, those owners who voluntarily quit their previous place of employment and report to be motivated by some opportunity. I classify spinouts as pursuing an opportunity if they report any of the following as their primary motive for starting their firm; i) *To earn higher income*, ii) *to pursue a good opportunity*, iii) *to pursue their career of choice*. Other possible motives include, to *supplement family income, only way to earn an income, required a more flexible schedule*. Figure A.3 shows the share of spinouts by cohort in the ENAMIN sample.

The ENAMIN also allows for identification of a spinout's growth expectations which can serve as a proxy for growth. I take respondent's answer to the following question: *"What is your plan to continue your business?"* and use it to account for the additional margin of selection introduced by the ENAMIN sample restrictions.[42] Those spinouts that respond with *"No Major Changes"* are said to have no expectations for growth in the future while all others are said to have positive growth expectations. Figure A.4 shows the share of spinouts with positive growth expectations by employer size. There is a clear gap between growth expectations between those spinouts from small firms and those from large firms. While all types of spinouts expect to grow less as they age, the initial gap persists over the life cycle reinforcing the positive relationship between spinout growth and employer size.

I can also identify self-reported spinout exit in the ENAMIN sample using a question which asks respondents if they "*plan to continue their business or activity in the following year*". Those that respond in the negative are said to be exiting - around 4% of the sample. These self-reported rates are much lower than those in the ENOE and those

[42]Respondents are asked to choose one of eight options; take out a loan, hire additional workers, partner with other businesses, move location, formalize their business, improve product/service quality, no major changes and other. All responses are translated from the original Spanish.

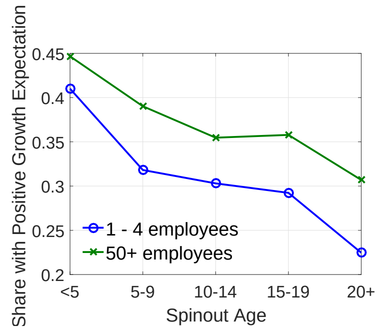


Figure A.4: Growth Expectations of Spinouts over the Lifecycle by Employer Size

Notes: Data is from the 2002 to 2012 ENAMIN sample.

reported in the literature. The difference is likely driven by the fact that firm exit is not typically planned or expected and exit in the ENAMIN sample is taken from self-reported plans to exit in the following year. What is important for analysis is not the level of exit but its relationship to employer size.

Table A.3 reports the results from estimating a probit regression under specification (2) using the ENAMIN sample and finds no statistically significant relationship between previous employer size and spinout exit. Similarly, conditional income in employment and job tenure have a negative but statistically insignificant impact on likelihood of exit.

Table A.3: Marginal Effects of Employer Size on Probability of Exit in the ENAMIN

	(1) P_i^{exit}	(2) P_i^{exit}
Employer Size		
▷ 5 to 49	-0.001	-0.000
	(0.006)	(0.008)
▷ 50+	0.007	0.013
	(0.007)	(0.011)
Conditional Income in Employment		-0.005
	-	(0.005)
Tenure with Employer (years)		-0.000
	-	(0.001)
Pseudo R^2	0.052	0.086
N	5,401	2,643

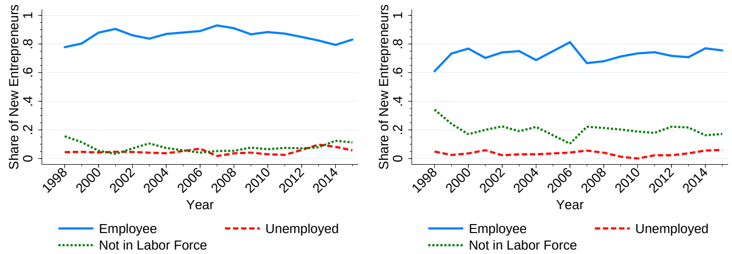
Notes: The omitted variable the dummy for spinouts from small employers, that is those with 1-4 employees. The ENAMIN probit regressions are estimated following specification (2) with the dependent variable being probability of reporting exit in the following year. Standard errors are reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1

A.2 Evidence from the US

This section presents empirical evidence on spinout entry, growth and exit using data from the 1997-2015 Current Population Survey (CPS) and the 1996, 2001, 04 and 08 Survey of Income and Program Participation (SIPP). Both these data sets are at the individual level and allow for individuals to be tracked from between a year and five years. As such, these data are most suitable for analyzing spinout entry and size at entry and not longer term spinout growth and exit.

I begin by briefly describing the CPS data which is used to study spinout entry by firm size in the US[43]. As with the ENOE, I exploit the rotating panel nature of the CPS to match respondents of the March Annual Social and Economic Conditions (ASEC) supplement to the CPS form 1997 to 2015. Figure A.5 shows the transitions into entrepreneurship in the CPS data and highlights, as in Mexico, that a majority of new entrepreneurs are spinouts formed by former employees. Spinouts are identified as former male employees between the ages of 18 and 65 who were employed full-time in a private, non-agricultural sector and transitioned into entrepreneurship between successive ASEC surveys. Unlike the ENOE, the CPS does not include detailed questions on why an individual switches occupations, limiting

[43] All CPS data is extracted from IPUMS and is available here https://cps.ipums.org/cps/



(a) Male (b) Female

Figure A.5: Annual transitions rate for new entrepreneurs in the CPS

Notes: Data is from the matched March CPS data covering 1997-2015. Sample includes males between the ages of 18 and 65.

our ability to ensure that only true transitions from employment to entrepreneurship take place. Instead, CPS respondents report the number of weeks that they were searching for work in the previous year (WKSUNEM1 in the IPUMS data). Those respondents that experience intervening period of unemployment between surveys are precluded from being classified as spinouts. The final sample size consists of 52,924 individuals.

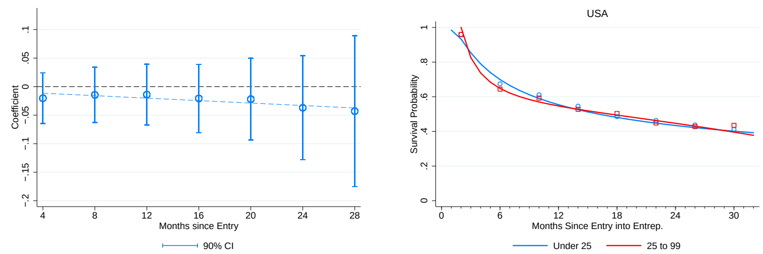
Spinout Entry Table A.4 reports the marginal effects from a probit regression of spinout entry and employer size in the CPS sample after the restrictions above have been applied. The dependent variable of the regression is an indicator that identifies spinouts. The first column controls for industry and demographics and illustrates a negative relationship between employer size and likelihood of spinout entry in the US. The second column includes log income as an explanatory variable and shows that the negative relationship in firm size and spinout entry persists and that more able individuals (ability as proxied by income) are more likely to enter as spinouts. While there are differences in levels between the US and Mexico, both economies display a strikingly similar relationship between employer size and spinout entry.

Table A.4: Marginal Effects of Employer Size and Probability of Entry as Spinout in the CPS

	(1) *Pr(Spinout)*	(2) *Pr(Spinout)*
Employer Size:		
< 10	0.086***	0.088***
	(0.005)	(0.005)
10 to 49	0.030***	0.031***
	(0.004)	(0.004)
50 to 99	0.020***	0.020***
	(0.002)	(0.002)
100 to 499	0.010***	0.007***
	(0.002)	(0.002)
$Income_{emp}$ (Log, 2010USD)	-	0.003***
	-	(0.001)
Pseudo R^2	0.156	0.157
N	33,741	33,741

Notes: The omitted variable for employer size is the dummy for employers with more than 500 employees. All probit regressions control for industry, year, and state fixed effects.Demographic controls include a quadratic in total years of experience and education bins which correspond to those with less than a HS degree, those with a HS degree, those with at least a college degree and those with at least a HS but no college degree. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Spinout Size To asses the relationship between employer and spinout size, I rely on panel data available in the SIPP. Under the same sample restrictions as the CPS, the SIPP data enables us to track spinout performance beyond



(a) Spinout Growth, coefficient γ_t (b) Probability of Exit

Figure A.6: Employer Size and Spinout Growth and Exit in the SIPP

Notes: Data is from the combined SIPP 1996,2001,04, and 08 panels. Sample only includes males between the ages of 18-65 that transitioned from full-time, private, non-agricultural employment to entrepreneurship.

entry. However, there are several limitations to using the SIPP data for tracking spinout performance over the lifecycle which I discuss below. Spinouts are identified using the same sample restrictions as those for the CPS. However, since data on SIPP respondents is available at a monthly frequency, I consider only quarterly transitions. Furthermore, given the attrition in the SIPP I restrict the sample to include those individuals for whom I have at least 8 months of information [44].

Given these sample restrictions, I use the business income of the spinout owner as a measure of firm size and study how employer size impacts this measure up to 28 months after spinout entry. Notice, the SIPP data does not report exact number of employees and groups firm size into three broad bins; <25 employees, 25-99 employees and 100+ employees [45]. To assess the impact of employer size on spinout income I perform the following regression:

$$log(income_t) = \alpha_t + \beta_t X + \gamma_t \mathbb{I}(employer\ size =< 25\ employees)$$

where t denotes months since entry and the vector X contains controls for industry, year and demographics. Demographic controls include dummies for education, quadratic in years of experience and state level fixed effects. The coefficient γ captures the impact of employer size on spinout owner's income. In particular, given the evidence on Mexico I expect $\gamma_t < 0$ for all t and also that $\gamma_{t+1} < \gamma_t$. Figure A.6a plots γ_t and the 90% confidence interval and shows that this coefficient is indeed negative and decreasing in months since entry. However, it is not statistically different from 0 for any period. There are several reasons why this might be the case. Firstly, and perhaps most importantly, the firm size bins in the SIPP are very large. For instance, according to the Business Dynamics Statistics (BDS) database 88% of all employer firms in 2015 hire fewer than 20 employees. This along with the relatively small sample size in the SIPP makes this data less than ideal to study spinout performance by employer size and can explain the large confidence intervals in figure A.6a.

Spinout Exit To study exit, I use data from the SIPP to first identify spinouts as above and then compute the share of those that do not continue their enterprise into the following month. Figure A.6b plots the share of continuing spinouts by previous employer size up to 32 months following entry. The figure shows that there are no differences in likelihood of spinout exit by employer size. This mirrors the relationship between employer size and spinout exit observed in Mexico.

[44] After making these restrictions, I am left with a sample of 24,799 monthly observations from 909 individuals who form spinouts.

[45] Using spinout profit as a measure of size yields qualitatively similar results.

B Computational Details

Stationary Equilibrium

This section describes the computational details involved in solving the model. I create a log-spaced productivity grid z using 180 grid points. Increasing the number of grid points did not significantly change the equilibrium solution. Figure A.7 compares the model and data's firm size distribution.

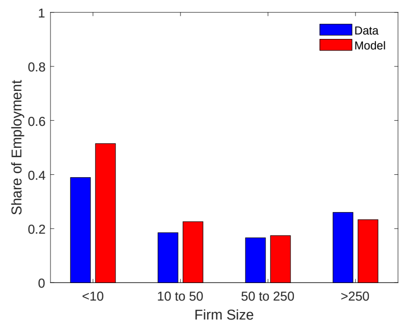


Figure A.7: Employment Weighted Firm Size Distribution

Notes: Data is from the 2014 Economic Census in Mexico as reported by INEGI.

Since employee and employer sorting is random, computing the value in employment involved taking expectations over the probability of a worker being employed by a particular employee. However, these probabilities are a function of the stationary distribution $\Psi(z)$. So, in order to solve the model, I do not only make a guess for wages $\tilde{w}$, as is standard, but also need to make an initial guess for the stationary distribution, $\tilde{\Psi}_0$. Then, to solve for the invariant distribution I construct a transition matrix $\Gamma\left(\tilde{w},\tilde{\Psi}_0\right)$ implied by $\tilde{w},\tilde{\Psi}_0$. Then, I can forward iterate on $\tilde{\Psi}_0$ using $\Gamma(\cdot)$ with the additional step of reconstructing the transition matrix with each iteration. In particular, I solve for the fixed point problem$\tilde{\Psi}_{n+1}=\Gamma\left(\tilde{w},\tilde{\Psi}_n\right)\tilde{\Psi}_n$ and terminate when $\tilde{\Psi}_{n+1}\approx\tilde{\Psi}_n$.

With this additional step in mind, the solution algorithm is as follows:

1. Guess a wage $\tilde{w}$
2. Given wage, use value function iteration to solve for the value functions $V^e(z)$ and $V^w(x;z)$ for entrepreneurs and workers respectively.
3. Guess a distribution $\tilde{\Psi}_0$ in order to compute the return to being a worker $W(z)=\int V^w(x;z')\frac{l(z')}{\int l(s)d\tilde{\Psi}_0(s)}d\tilde{\Psi}_0(z')$
4. Given $\tilde{w}$ and $\tilde{\Psi}_0(z)$ solve for the optimal occupation, investment and learning choices of agents.
5. Iterate for the stationary distribution $\tilde{\Psi}_1(z)$ implied by optimal policy rules and as described above.
6. Check for labor market clearing. If not, return to step 1 adjusting guess for wage and using $\tilde{\Psi}_0(z)=\tilde{\Psi}_1(z)$.

I chose the exogenous distribution $F(z)$ as the initial guess $\tilde{\Psi}_0$ and found that results were unchanged when using single mass point or uniform distributions.

Perfect Foresight Transition

The parameters for the model without learning are shown in table **??**. Notice, that spinouts are driven only exogenously via $\delta_w$which is chosen to match the aggregate spinout rate.

Table B.5: Parameters of the Model with No Learning

Parameter	Value	Basis
	Pre-determined	
β	0.94	Annual Interest Rate
θ	0	See text
	Calibrated	
Δ	1.11	SD of Empl. Growth
η	0.56	Top 1% Income Share
μ	4.1×10^{-4}	Empl. Age 20 relative to Age 5
ϕ_e	9.1	Share of Entrepreneurs
δ_e	0.28	Exit Rate in ENOE
δ_w	0.17	Aggregate Spinout Rate
Pareto Tail, γ	1.31	Top 5% Empl. Share

The algorithm to solve for the transition dynamics of the benchmark model involves, once again, guessing for the equilibrium distribution Ψ. However, in this case, the sequence of distributions along the transition paths must be guessed and be such that they are consistent with the law of motion of productivity. The solution algorithm for the transition dynamics from time 0 to T is as follows:

1. Guess a sequence of wages $\{w_t\}_{t=0}^T$
2. Guess a sequence of distribution $\{\Psi_t\}_{t=0}^T$
3. Solve by backward induction, the value functions $V_t^e(z)$ and $V_t^w(x;z)$
4. Using the guess of distributions $\{\Psi_t\}_{t=0}^T$ solve for $W_t(z)$
5. Check if the sequence of $\{\Psi_t\}_{t=0}^T$ satisfies the laws of motion all along the transition path.
6. If not, updated the sequence of distribution and start from step 3.
7. Otherwise, check if labor markets clear and update wage sequence $\{w_t\}_{t=0}^T$ accordingly.

The initial guess of distributions was assumed to be the stationary distribution. Experimenting with the uniform distribution did not lead to changes.