EMPLOYER SIZE AND SPINOUT DYNAMICS*

Faisal Sohail†

Washington University in St. Louis

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Abstract

Most new firms are founded by former employees of existing firms - spinouts. This paper studies the relationship between employer size and spinout entry, size and growth. Using micro-data from Mexico, we document a negative relationship between employer size and spinout entry. That is, employees from small firms are more likely to form spinouts than those from large firms. Second, we uncover a positive relationship between employer size and spinout size both at entry and over the lifecycle. Spinouts from large employers start at a larger scale and grow faster than spinouts from small employers. Although a qualitatively similar relationship is observed in data from the U.S., there are large quantitative differences in the levels of spinout formation. To understand the impact of these differences on aggregate outcomes, we build a model of occupational choice and firm dynamics in which workers can learn from and adopt the productivity of their employers to form their own firms. In this framework, differences in the rates of spinout formation between Mexico and the U.S. are driven by differences in the efficiency with which employees learn from their employers. We interpret this efficiency as representing a form of managerial quality. The model, calibrated to match spinout entry rates across the two countries, can account for 13 and 19% of the cross-country variation in output per worker and firm growth respectively. These findings highlight the relevance of spinouts for aggregate outcomes, and the potential for managerial quality to not only impact incumbent firms but also future entrants.

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

JEL Codes: J24, L25, N16, O11, D83,

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†Ph.D. Candidate, Economics, Washington University in St. Louis. 1 Brookings Drive, Box 1208, St. Louis MO 63130. Email: sohailf@wustl.edu

1 Introduction

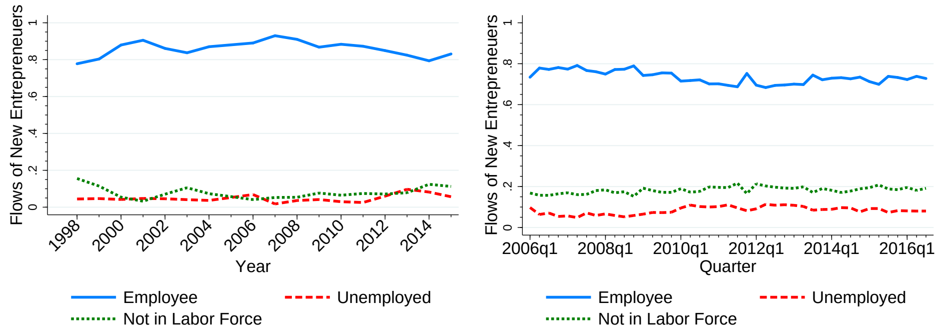
Spinouts are those business ventures that are founded by former employees of existing firms[1] and account for a majority of all new entrepreneurs in both Mexico and the United States (U.S.), as shown in figure 1. Since the formation and subsequent success of firms contribute significantly to output and productivity[2], identifying the determinants of firm entry, size and growth is important for understanding aggregate outcomes within and across economies.

This paper's contribution to this understanding is twofold. First, we provide evidence from Mexico establishing that employer productivity - proxied via the number of employees - is *negatively* correlated with spinout entry and *positively* correlated with spinout size and growth. In particular, using individual level data to track transitions from employment to entrepreneurship, we show that employees of firms with at most 4 employees are 7 times more likely to form spinouts within a year than employees of firms with over 500 employees. This finding is robust to a variety of employer and employee level controls and can not be explained by differences in separation rates across employers of varying sizes. Interestingly, we find a positive relationship between employee ability (proxied by income in employment) and spinout entry. To study spinout performance following entry, we use firm-level data from a nationally representative sample of small firms in Mexico. Using this data, we show that spinouts from smaller firms not only start small, but experience flatter age-size profiles over their lifecycle. More specifically, 20 years after entry, spinouts from firms with at most 4 employees exhibit 5%, 25%, and 45% lower productivity, wage bill and capital stock, respectively, than spinouts from firms with greater than 50 employees. As with spinout entry, this finding is robust to a variety of definitions of size, as well as industry and individual controls. We interpret these findings as supporting a theory of knowledge diffusion between employers and employees. Comparing the findings from Mexico with those from the U.S. yields a qualitatively similar relationship between employer size and spinout dynamics. However, we observe large quantitative differences in the rates of spinout formation and find that employees are 3 times more likely to form spinouts in Mexico than in the US.

Motivated by this evidence, the second contribution of this paper is to quantitatively explore the role of spinouts in driving differences in output, firm size, growth and entrepreneurship between U.S. and Mexico. To this end, we build a model of occupational choice and firm dynamics that reconciles the qualitative relationship between employer size and spinouts. In the model, agents that are heterogeneous in productivity choose between entrepreneurship and employment. Entrepreneurs hire workers and invest to improve their own productivity. Workers are employed by entrepreneurs and can choose to learn from and adopt the productivity of their employers to form spinouts. A novel feature of this model is the assumption that the cost of employee learning is increases in the relative gap between employee and employer productivity. This feature

[1]Spinouts are distinct from *spinoffs* since the latter term typically refers to those firms that are founded by employees within the same industry as their prior employer. Throughout this paper, we will refer to spinouts as any firm founded by former employees of existing firms regardless of their employer's industry.

[2]See for example Foster et al. (2001) and Asturias et al. (2017)



(a) U.S.

(b) Mexico

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.

captures the intuitive notion that more productive workers are better able to learn from a given employer and that it is easier for all workers to learn from a low productivity employer. When calibrated to match salient features of the Mexican economy, the model delivers a negative relationship between employer size and spinout entry in the stationary equilibrium. The model also features differences in spinout growth by employer size. These differences are due to the option value of learning in employment. In particular, the ability to learn as a worker lowers the incentives to innovate as an entrepreneur, especially for marginal entrepreneurs. This results in more productive firms, investing more in productivity growth than less productive firms. Since spinouts exactly replicate their employer's productivity, spinouts generated from larger firms grow faster than those from smaller firms, as observed in the data.

This framework is used to quantitatively assess the impact of spinouts on aggregate outcomes. This analysis is motivated by the observed differences in spinout formation in the U.S. and Mexico. We begin by considering two channels as explanations for differences in spinout formation; i) aggregate productivity and ii) the efficiency with which workers learn from employers. We interpret the latter as representing a particular form of managerial quality. Namely, those management practices that pertain to the development of employee productivity through monitoring and review. In the model, better management is reflected as a decrease in the cost of adopting employer productivity. In contrast, aggregate productivity is interpreted as capturing, among other factors, management practices that impact firm productivity only. A quantitative exercise shows that differences in aggregate productivity alone cannot explain the cross-country differences in spinout formation. In fact, when calibrated to match output per worker, aggregate productivity differences account for only 29%, 50% and 9% of the observed cross-country variation in spinout rates, entrepreneurship, and firm growth, respectively. Motivated by this result, we calibrate the efficiency in productivity adoption to match the observed spinout formation rates. We find that this factor alone accounts for 13% of the observed gap in output per worker and can fully explain the gap in both average firm size and entrepreneurship, as well as 19% of the gap in firm growth between US and Mexico. These results highlight the potential of management practices in impacting not only incumbent firms but also future entrants. Taken together, these findings highlight the importance of incorporating spinout entry, size and growth in order to understand aggregate outcomes. Indeed, when we allow both aggregate productivity and learning efficiency to vary, the model economy outperforms the version when only one of the two factors vary.

Related Literature This paper contributes to several strands of literature. First, we add to and extend the existing empirical literature on spinout entry and it's 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 datasets and find a negative relationship between employer size and spinout entry. Findings on the relationship between employer size and spinout performance are mixed with studies documenting either a negative or positive relationship. This paper is the first to study spinouts in the Mexican context. While the findings on spinout entry and employer size are consistent with existing work, this paper is the first to use firm level data to study the performance of spinouts up to 20 years after entry. Andersson and Klepper (2013) are 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.

The Mexican data has several advantages that make it ideal to study spinouts across countries. First, it includes information on both formal and informal activity. This is particularly important given the large informal sector in many developing economies[3]. In contrast, Muendler et al. (2012) also study spinouts in a developing economy but only observe employers and spinouts in the formal sector. Another advantage of the data from Mexico is that it allows for a clear identification of a firm's founders and their work history including spells of unemployment and reasons for pursuing entrepreneurship. As a result, we do not rely on rules to infer firm founders and are able to construct samples that are consistent across both Mexico and the U.S.

This paper is also related to the theoretical literature on knowledge diffusion between employers and employees and the formation of spinouts. Early work includes Franco and Filson (2006) who also focus on the ability of employees to learn from their employers. More recently, Baslandze (2017) extends their framework and studies the interaction of non-compete laws and the innovation incentives of existing firms. However, these papers are motivated by empirical evidence from a single industry or a narrow set of firms [4] and document a *positive* relationship between spinout entry and employer size. The resulting models built by these authors replicate this positive relationship and are not consistent with the country-level evidence. The model in this paper

[3]See for example La Porta and Shleifer (2014)

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

introduces employee learning in an occupational choice framework which features firm dynamics. Learning in this framework is distinct from existing works such as Roys and Seshadri (2013) and Lucas Jr and Moll (2014) since we assume that learning is not only a function of an agent's own productivity but also that of their employer.

Finally, this paper is relevant for the growing literature that studies the impact of management practices on firm and aggregate outcomes. Much of this literature investigates the role of management through randomized controlled trials (e.g. Bruhn et al. (2013); Brooks et al. (2016); Bloom et al. (2013)), the empirical and theoretical findings in this paper can serve as a guide for interventions aimed at improving management practices. In particular, we find the impact of good management on a firm's employees to be relevant for aggregate outcomes such as the creation, size and growth of new firms.

An outline of the paper is as follows: Section 2 details the empirical evidence in the Mexican economy. Section 3 presents the model. Section 4 describes the calibration and the model's fit to the data. Section 5 outlines the interpretation and results of the quantitative exercise and section 6 concludes. Evidence from the U.S. along with details of the data is presented in the data appendix.

2 Empirical Evidence

This section details the empirical evidence on spinout entry, performance and exit in Mexico. First, using data individual level data, we study the negative relationship between employer size and spinout entry. Second, using firm level data, we document a positive relationship between employer size and various measures of spinout size both at entry and over the lifecycle. Finally, we discuss the relationship between spinout exit and employer size. Analogous evidence based on U.S. data is presented in section A.2 of the appendix.

Before presenting this evidence in detail, we briefly describe the data.

Data Description Individual level data is taken from the 2005Q1 to 2016Q3 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 analog to the Current Population Survey (CPS) conducted in the US in both the questions asked and in it's design. Like the CPS, the ENOE serves as an important resource in measuring the status of Mexico's labor force [5]. Participants in the ENOE are interviewed at most 5 times over 5 consecutive quarters. By exploiting the rotating panel nature of this data, we match individuals across quarters to track flows between employment, entrepreneurship and non-employment[6]. Spinouts are identified

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

[6] 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

as those individuals who transition from employment in full time, 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, we exclude those respondents that experienced periods of non-employment in the intervening quarters as being spinouts. The final sample includes over 2 million survey responses from over 574,000 unique individuals. Additional details are available in the appendix.

Firm level data is from the National Survey of Micro-Businesses *(Encuesta Nacional de Micronegocios*, ENAMIN) covering 8 years between 1992 and 2012[7]. Participants in the ENAMIN are firm owners that have up to 15 employees if in the manufacturing sector and up to 10 employees otherwise[8]. The survey includes detailed questions about firm's activities, as well as the founder and their prior work history. We identify spinouts as being those firms that were founded solely by former employees who voluntarily left their last position. We only include former employees that were employed in the private, non-agricultural sector and earning at least the mandated minimum wage. Details on the ENAMIN sample restrictions are described in the appendix.

2.1 Spinout Entry

We begin by establishing a negative relationship between the probability of starting a spinout and employer size in Mexico. Figure 2 shows this negative relationship in the matched ENOE sample. 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 employer size for each size bin reported in the ENOE. In the data appendix, we show that the relationship between employer size and spinout entry is nearly identical in Mexico as in the U.S. This suggests a common, fundamental phenomenon that drives the negative relationship and is common across economies. Existing work has focused on theories of selection or treatment. Each theory has distinct predictions that can be empirically tested in the ENOE data. An important prediction of the selection theory is that individual characteristics such as, unobserved ability, explain the relationship in figure 2. To test this, we perform a probit regression which includes controls for industry, informality of prior employment, demographics, state and year fixed effects on an indicator variable which is equal to 1 if an employer entered as a spinout -*Pr(Spinout)*. Column (1) of table 1 shows the results from this regression. The second column shows that including income earned in employment, a proxy for unobserved individual ability, does not change the negative relationship between employer size and spinout entry. Furthermore, unobserved ability is positively associated with spinout entry with an additional 1%

from 2005Q1 to 2016Q3 the average match rate is 80% and the sample, prior to any restrictions includes 3.01 million matched interviews from 1.65 million unique individuals.

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

[8]In the ENOE sample 95.3(97.47)% of all employers hire at most 10(15) employees. This is in line with Hsieh and Olken (2014) who use census data to show that 91.7% of all firms in Mexico hire at most 9 employees. ENAMIN surveys prior to 2002 include only those firms which have up to 5 employees if not in the manufacturing sector.

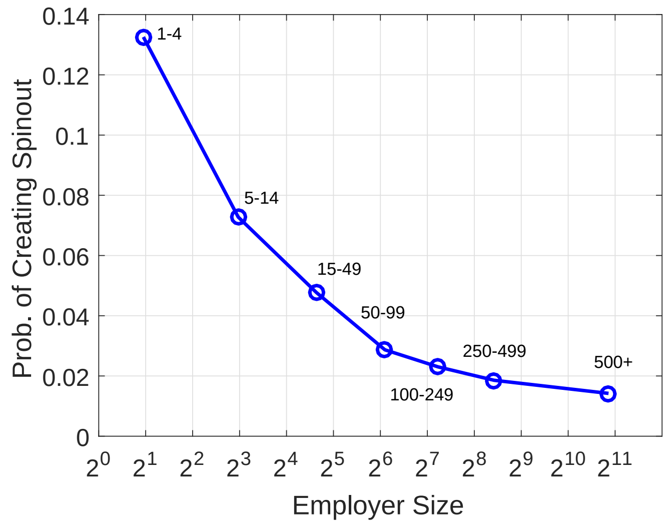


Figure 2: Probability of Entering as Spinout

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).

change in monthly income leading to a 2% increase in the likelihood of spinout entry. The third column includes job tenure with the previous employer as an explanatory variable and shows that it is also positively associated with spinout entry[9]. An additional 5 years with an employer lead to a 1.5% increase in the likelihood of spinout entry.

Notice, it may be possible that the findings above do not reflect differences in likelihood of spinouts but differences in any form of separation from employment across employer size. If separations from employment are more prevalent in small rather than large firms, then the negative relationship between spinout entry and employer size may simply reflect this difference. One approach to address this concern is to exclude all employees who experience unemployment, as is done the ENOE sample. Alternatively, we may also study whether separations are indeed more prevalent in small firms and if, conditional on separating, employees from smaller firms are equally likely to form spinouts as those from larger firms. Table 2 shows the transitions of all employees in year y to year $y+1$ by prior employer size. It highlights that separations are indeed negatively associated with employer size. However, the last column of table 2 shows that, 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 explain the negative relationship between employer size and spinout entry.

[9] Data on job tenure is only available in the extended ENOE sample which has been conducted only once a year since 2006.

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

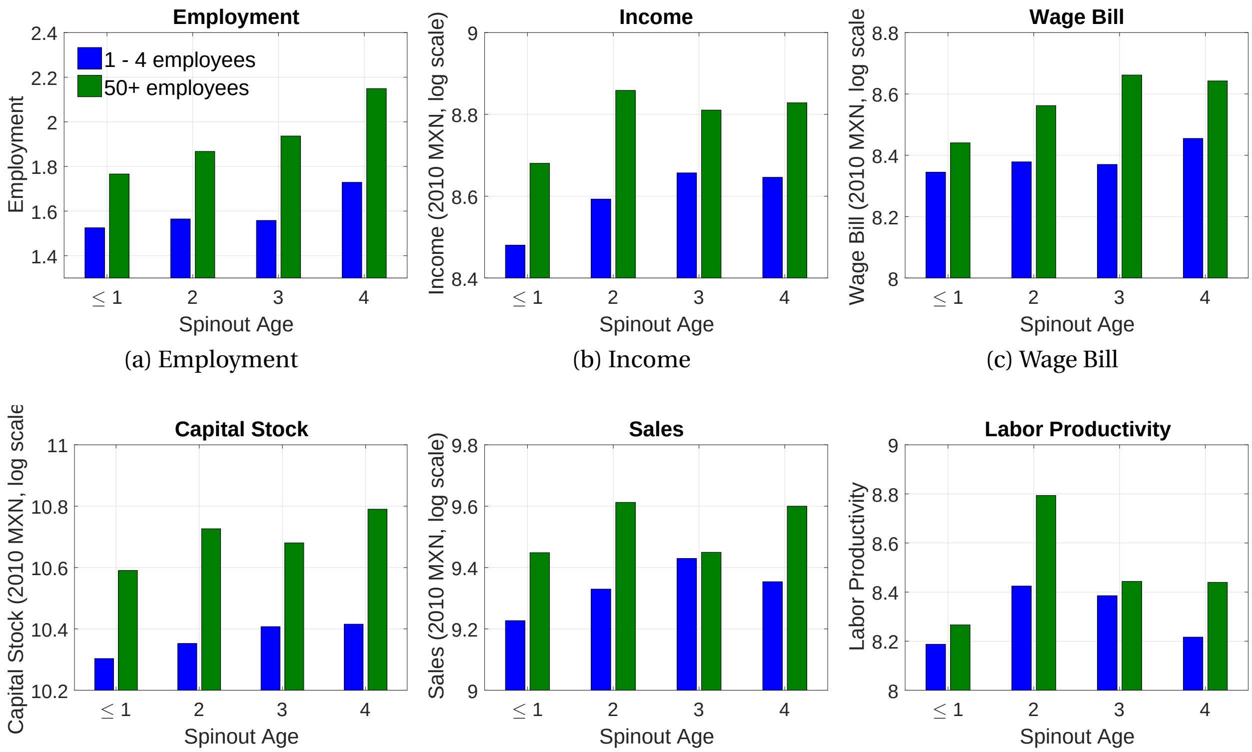
	(1) *Pr(Spinout)*	(2) *Pr(Spinout)*	(3) *Pr(Spinout)*
Employer Size:			
2 to 5	0.083***	0.093***	0.103***
	(0.002)	(0.002)	(0.004)
6 to 10	0.053***	0.057***	0.059***
	(0.002)	(0.002)	(0.004)
11 to 15	0.031***	0.033***	0.037***
	(0.003)	(0.002)	(0.005)
16 to 50	0.022***	0.022***	0.025***
	(0.001)	(0.001)	(0.003)
$Income_{emp}$ (Log, 2010MXN)	-	0.021***	0.017***
	-	(0.001)	(0.003)
Tenure (years)	-	-	0.003***
	-	-	(0.000)
Pseudo R^2	0.087	0.114	0.135
N	174,945	174,804	46,875

Notes: The omitted variable for employer size is the dummy for those employers with more than 50 employees. All probit regressions control for industry, year, and state fixed effects. I also control for informality status of previous employer as well as demographic controls. 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. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 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	$\frac{(2)}{(2)+(3)+(4)}$
2 to 5	75.30	13.94	4.46	6.30	56.44
6 to 10	82.79	8.72	3.78	4.72	50.64
11 to 15	86.23	5.88	3.57	4.32	42.70
16 to 50	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).



(a) Employment (b) Income (c) Wage Bill

(d) Capital Stock (e) Sales (f) Labor Productivity

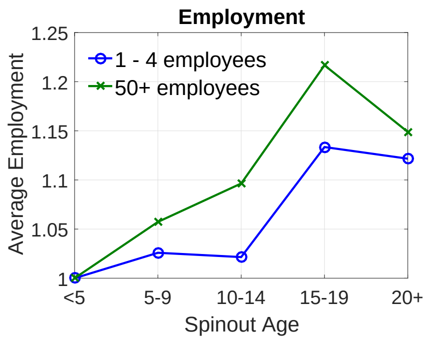
Figure 3: Spinout Performance at Entry

2.2 Spinout Size

Here, we consider the relationship between spinout size and employer size using firm level data from the ENAMIN. We use six measures of spinout performance to quantify the relationship between employer size and spinout quality both at entry and over the spinout's lifecycle. These measures are: i) number of employees, ii) owner's income, iii) wage bill, iv) capital stock, v) sales and vi) labor productivity.

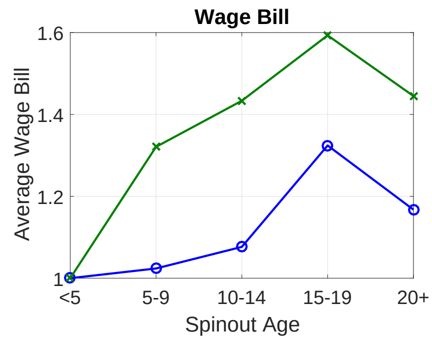
The panels in figure 3 show the average of these measures for young spinouts from small (1-4 employees) and large (50+) employers. In the initial year of operation, spinouts from large firms are 10-30% larger than spinouts from small firms. This gap grows, for most measures, by the fourth year of operation suggesting that that large firm spinouts perform better at entry than small firm spinouts. Figure 4 documents that a performance advantage persists over the lifecycle with spinouts from smaller firms experiencing a flatter age-size profile. Taken together, these figures indicate a positive relationship between employer size and spinout performance not only at entry but also over the lifecycle. A more systematic analysis of this relationship is performed by performing an OLS regression which controls for various explanatory factors with the following specification:

$$perf_i = \boldsymbol{\beta X}_i + [\sum \alpha_{sa}(EmployerSize_i = s) \times (SpinoutAge_i = a)] + \gamma\,(EmployerIndsutry_i = SpinoutIndustry_i) + \epsilon$$

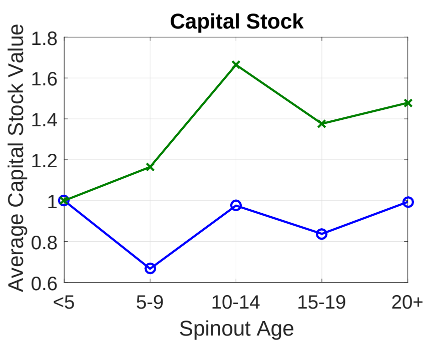


(a) Employment

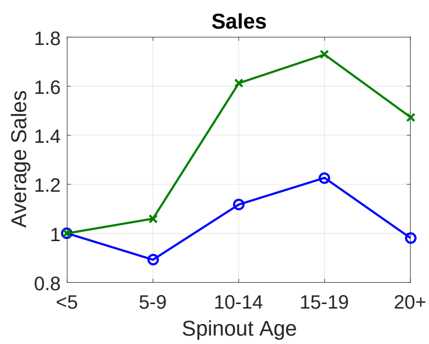
(b) Income



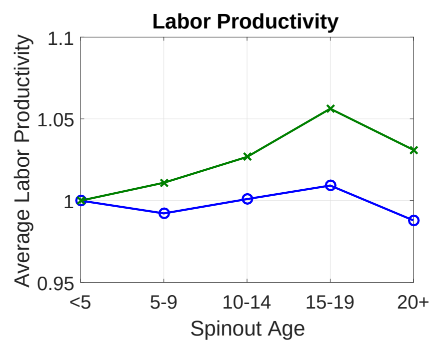
(c) Wage Bill



(d) Capital Stock



(e) Sales



(f) Labor Productivity

Figure 4: Spinout Size Over the Lifecycle

The dependent variable is the performance measure of a spinout founded by an individual i . The vector $\boldsymbol{X}$ contains controls for spinout industry (2 digit NAICS codes), spinout cohort fixed effects and individual fixed effects. Individual controls include a quadratic in years of experience, age and state dummies. There are three categories for employer size s and spinout age a. The coefficient γ captures the impact on performance of a spinout remaining in the same (2 digit) industry as their previous employer. Panel A of table 3 reports the coefficients α_{sa} and γ for the ENAMIN sample from 2002-2012. The omitted variable is the interaction term between spinouts older than 10 years of age that were founded by employees of large (50+ employer) firms. The coefficient on performance for spinouts from small (1-4 employees) employers shows that these spinouts are consistently smaller than the omitted group. This performance gap varies over the lifecycle, tending to grow, from between 27-53% at entry to 46-77% at maturity (age 10+). Spinouts from medium (5-49 employees) employers also exhibit this deficit in performance. However, for most measures of size, the gap in performance is not statistically significant. Spinouts from medium sized firms tend to be larger than spinouts from smaller firms at each point in the lifecycle with the size gap ranging from 0-33% at entry and 0-25% at maturity. Finally, and consistent with the figures above, spinouts from large firms tend to be larger at each point in their lifecycle. For instance, the gap in labor productivity between these spinouts is 14(6)% at entry and grows up to 37(15)% relative to spinouts from small(medium) sized firms. Overall, these results provide strong evidence supporting a positive relationship between employer size and spinout performance not only at entry but over the lifecycle.

Notice also that spinouts that remain in the same industry as their previous employer tend to be between 13% to 40% larger than those that do not remain in the same industry as their employer. This positive impact of remaining within an industry is consistent with the existing literature on spinouts[10] and we interpret it as reflecting a transfer of industry specific know-how that employees learn from their employer and utilize in their spinout. We provide further evidence for a theory of knowledge transfer by repeating the regression specification above and including job tenure as well as income earned in employment as additional explanatory variables. The coefficients on these two variables are shown in panel B of table 3. Both log income in employment and job tenure have a positive and statistically significant impact on spinout size for most measures of size. In particular, an additional 10 years of employment can lead to operating spinouts that are up to 18% larger. The positive relationship between tenure and spinout performance is interpreted as evidence supporting knowledge transfer between employees and employers. Having said this, the impact of higher income in employment, a proxy for unobserved ability, has a much larger impact on spinout size than tenure. Indeed, an additional 1% increase in income results in an up to 38% larger spinout. So, while there is evidence that employee learning is important for spinout performance, employee ability plays a larger role. As such, any theory of spinouts should incorporate both factors.

Before discussing spinout exit, it should be noted that the ENAMIN sample does not include large firms. This is problematic as many spinouts may grow to be ineligible for inclusion in the ENAMIN over their lifecycle. Of particular concern is the possibility that spinouts from small employers grow at *faster* rates than those from large employers. If this were the case then we should observe a lower share of spinouts spawned from small employers in the ENAMIN sample relative to those from large employers as spinouts age. Figure 5 shows that the share of spinouts from small(large) employers rises(falls) over the lifecycle. This is consistent with the positive relationship between employer size and spinout growth.

The ENAMIN also allows for identification of a spinout's growth expectations which can serve as a as a proxy for growth. We take respondent's answer to the following question: *"What is your plan to continue your business?"* [11] and use it to account for the additional margin of selection introduced by the ENAMIN sample restrictions. 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 6 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 lifecycle reinforcing the positive relationship

[10] See for example Andersson and Klepper (2013).

[11] 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.

Table 3: Spinout Size over the lifecycle by Employer Size

Panel A: Spinout Size and Employer Size

	(1) Employees	(2) Income	(3) Wage Bill	(4) Capital Stock	(5) Sales	(6) Labor Productivity
Employer Size						
<5 Years						
1 - 4	-0.396***	-0.269***	-0.461***	-0.531***	-0.399***	-0.430***
	(0.109)	(0.049)	(0.094)	(0.118)	(0.070)	(0.134)
5 - 49	-0.162	-0.052	-0.113	-0.385***	-0.157**	-0.339**
	(0.109)	(0.049)	(0.094)	(0.118)	(0.070)	(0.135)
50+	-0.178	0.019	-0.175*	-0.066	-0.058	-0.284**
	(0.113)	(0.052)	(0.098)	(0.124)	(0.074)	(0.140)
5 - 9 Years						
1 - 4	-0.441***	-0.315***	-0.502***	-0.749***	-0.499***	-0.557***
	(0.090)	(0.041)	(0.079)	(0.100)	(0.059)	(0.111)
5 - 49	0.053	-0.054	-0.044	-0.178*	-0.049	-0.256**
	(0.091)	(0.043)	(0.077)	(0.102)	(0.061)	(0.111)
50+	-0.175*	0.001	-0.162*	-0.250**	-0.034	-0.222*
	(0.098)	(0.046)	(0.084)	(0.111)	(0.066)	(0.122)
$\geq$ 10 Years						
1 - 4	-0.458***	-0.371***	-0.460***	-0.772***	-0.537***	-0.367***
	(0.064)	(0.030)	(0.056)	(0.073)	(0.042)	(0.078)
5 - 49	-0.029	-0.146***	-0.147***	-0.245***	-0.193***	-0.145*
	(0.067)	(0.031)	(0.056)	(0.076)	(0.045)	(0.081)
Same Industry "=1"	0.145***	0.235***	0.126***	0.396***	0.325***	0.168***
	(0.037)	(0.017)	(0.033)	(0.041)	(0.024)	(0.046)
Industry FE	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
N	8,121	11,087	4,099	7,924	10,587	3,804
R^2	0.050	0.128	0.078	0.171	0.103	0.059

Panel B: Impact of Income in Employment and Job Tenure

log($income_{emp}$)	0.171***	0.238***	0.220***	0.376***	0.298***	0.211***
	(0.030)	(0.011)	(0.026)	(0.029)	(0.016)	(0.035)
Job Tenure (years)	0.006*	0.004***	0.000	0.018***	0.006***	-0.003
	(-0.003)	(-0.001)	(-0.003)	(-0.004)	(-0.002)	(-0.004)
N	5,164	9,973	3,747	7,157	9,535	3,460
R^2	0.057	0.144	0.082	0.184	0.117	0.066

Notes: Data is from the 2002-2012 ENAMIN samples. Panel A displays displays the coefficients from the following OLS regression: $perf_i = \boldsymbol{\beta X}_i + [\sum \alpha_{sa}(EmployerSize_i = s) \times (SpinoutAge_i = a)] + \gamma\,(EmployerIndsutry_i = SpinoutIndustry_i) + \epsilon$. Panel B reports the coefficients on job tenure and income in employment. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

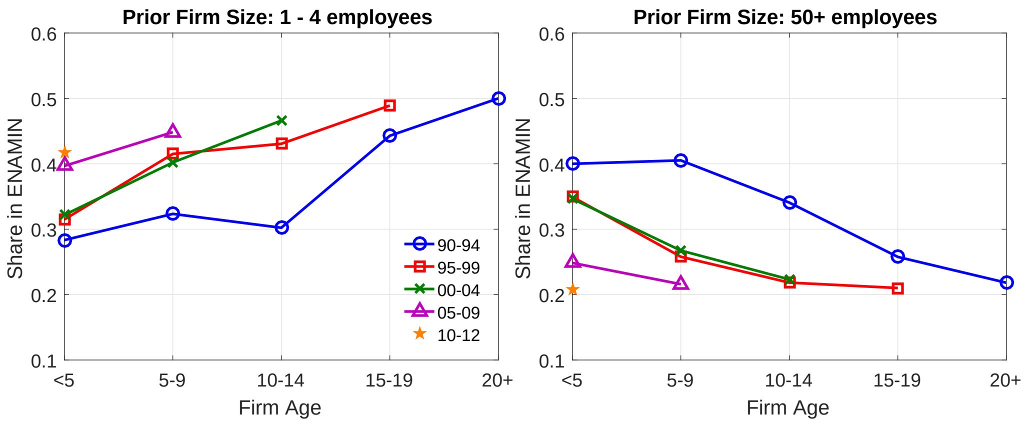


Figure 5: Share of ENAMIN Sample by Cohort and Employer Size

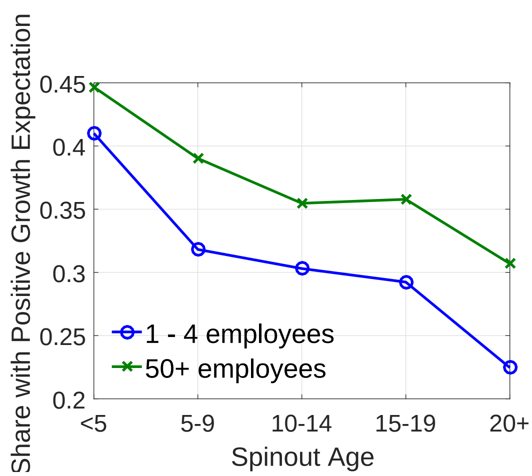


Figure 6: Growth Expectations of Spinouts over the Lifecycle by Employer Size

between spinout growth and employer size.

2.3 Spinout Exit

The empirical analysis thus far has ignored an important component of spinout dynamics, that is, exit of spinouts. Here I consider the relationship between employer size and likelihood of spinout exit. Due to the limited number of observations for each individual, the ENOE is not well suited to this analysis. Similarly, the ENAMIN sample contains only existing firms and does not survey those that exit. However, the ENAMIN does ask respondent's if they *"plan to continue their business or activity in the following year"*. In the sample, 6.9% of spinouts intend on exiting in the following year [12].

We test the relationship between employer size and spinout exit by performing a probit regression on an indicator variable to identify those that exit. Table 4 shows the results for four specifications of this regression. For all specifications the indicator for large (50+ employees) employers

Table 4: Employer Size and Probability of Spinout Exit

	(1) Pr(Exit)	(2) Pr(Exit)	(3) Pr(Exit)	(4) Pr(Exit)
Employer Size				
1 to 4	-0.135*	-0.117	-0.088	-0.076
	(0.081)	(0.087)	(0.100)	(0.106)
5 to 49	0.063	0.084	0.095	0.152
	(0.079)	(0.083)	(0.092)	(0.097)
Income as Employee (Log 2010MXN)	-	-	0.044	0.052
	-	-	(0.031)	(0.033)
Tenure (Years)	-	-	-	-0.005
	-	-	-	(0.007)
Industry FE	N	Y	Y	Y
Individual FE	N	Y	Y	Y
Cohort FE	N	Y	Y	Y
State FE	N	Y	Y	Y
Observed Prob	0.07	0.07	0.07	0.07
Pseudo R^2	0.00	0.03	0.03	0.04
N	3,780	3,580	2,910	2,632

Notes: Data is from the 2002-2012 ENAMIN sample. The table shows the marginal effects, obtained from a probit regression, of employer size, income in employment, and tenure in employment on probability of spinout exit. The reference employer size category is employers with more than 50 employees.

is omitted. The first column tests the impact of employer size on exit with no other controls and finds that spinouts from small firms are less likely to exit than those from larger and medium sized firms. Interestingly, the coefficient on medium sized firms is positive but not statistically significant. Including controls for industry, individual, cohort and state results in the same relationship but it is not statistically significant, as seen in the second column. Further controlling

[12] This is lower than the exit rate of over 30% reported by Fajnzylber et al. (2006) for small firms in Mexico. This gap is very likely driven by the fact that most firm exit is not expected and the ENAMIN sample only asks respondents about their expected likelihood of exit. What is important for our analysis is not the level of exit but it's relationship to employer size.

for income and tenure in columns three and four results also results in a statistically insignificant coefficients. In sum, there is no systematic relationship between employer size and spinout exit.

3 Model

The model economy consists of a unit continuum of agents that are heterogeneous in their productivity to operate a firm. Agents are risk neutral and make an occupational choice in each period between working for a fixed wage or operating a firm. In entrepreneurship, agents hire workers, invest in their productivity and are faced with idiosyncratic productivity shocks which drive firm exit. This introduces 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 adopt the productivity of their employer and form spinouts. This effort is costly and depends not only on the employer but also the worker's own productivity. The formation of employee spinouts introduces the second endogenous source of productivity evolution and will be the focus of the quantitative exercises. In particular, I will show how changes in the efficiency with which workers learn from employers can drive aggregate outcomes along the same magnitude as changes in aggregate efficiency. The remainder of this section details the model and describes the stationary equilibrium which will be the focus of the quantitative analysis.

3.1 Entrepreneur's Problem

Time is discrete and agents are heterogeneous in idiosyncratic productivity z. In entrepreneurship, agents operate a decreasing returns to scale production function by hiring labor $l_t(z)$ and paying a fixed wage w_t determined in equilibrium. Profit $\pi_t(z)$ solves the following static maximization problem. :

$$\pi_t(z) = \max_l \ Az^{1-\eta} l_t(z)^\eta - wl_t(z)$$

where η determines the span of control of entrepreneurs and A is the aggregate productivity that varies across economies. Since we focus on the stationary equilibrium we will drop the time subscript t. Solving for the optimal labor choice yields both labor and profit linear in productivity given by:

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

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

In addition to earning profit, entrepreneurs must also choose how much to invest in their productivity which can determine their occupational choice and value in the following period. The form of productivity adoption is similar to that in Buera and Fattal-Jaef (2015). Investments in productivity are costly and it's outcome follows a binomial process, the expected value of which is chosen by entrepreneurs. In particular, agents choose the probability p with which their productivity is upgraded from it's current level z to $z\gamma$ where $\gamma > 1$. With probability $1-p$ there is no change in productivity. The cost of of achieving a probability p is given in terms of the final good and specified via the following cost function:

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

The investment cost function $i(p,z)$ is strictly increasing in z as in Atkeson and Burstein (2010). This ensures that Gibrat's law holds for large firms, that is, the growth rate is independent of firm size for large firms. Notice also that since there is no downgrading, all firm exit is exogenous and driven exclusively by exogenous idiosyncratic productivity shocks which occur with probability δ.

Having described the static maximization and investment problem, we can write the recursive optimization problem for employers:

$$V^e(z) = \max_p \pi(z) - i(p,z) + \beta(1-\delta)\left[pV(z\gamma) + (1-p)V(z)\right] + \beta\delta \int V(z')dF(z')$$

where $F(z)$ is an exogenous and stationary distribution. The value of an entrepreneur of productivity z is $V^e(z)$ 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 which I describe below.

3.2 Worker's Problem

Workers earn the market wage w and choose how much effort to exert in order to learn and adopt the productivity of their employers. This effort is costly and depends on the productivity of the worker (denoted by x), the employer's productivity z and the worker's choice variable q - the probability with which the worker's productivity in the next period becomes z (with probability $1-q$ there is no change in worker's productivity). The effort cost is assumed to have the following functional form:

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

This cost $c(\cdot)$ is increasing in the difference between worker and employer productivity. This assumption captures the 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 income) are more likely to form spinouts. Notice that $c(q,z,x)$ may be convex in $(z-x)$ and that it is convex in q. The value $V^w(x;z)$ for a worker of productivity x to be employed by an employer z is given by:

$$V^w(x;z) = \max_q w - Mc(q,z,x) + \beta\left[qV(z) + (1-q)V(x)\right]$$

where M denotes the efficiency with which workers are able to form spinouts.

In order to fully characterize the value in employment, we need to specify the assignment of workers to employers. We assume a uniform assignment of workers across employers, that is, workers are randomly allocated across employers. If we specify the endogenous stationary distribution to be $\Psi(z)$, then the value in employment for an agent of productivity x is given by:

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

Given the value in entrepreneurship and employment, the value $V(z)$ of an agent of productivity z is simply:

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

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

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

3.3 Equilibrium

We will 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*

$$\int l(z)\cdot o(z)\cdot d\Psi(z) = \int (1-o(z))\cdot d\Psi(z)$$

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

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

$$i_p(p,z) = \beta(1-\delta)\left[V(z\gamma) - V(z)\right]$$

$$c_q(q,z,x) = \beta\left[V(z) - V(x)\right]$$

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

$$\begin{aligned}\Psi_{t+1}(z) = \Psi_t(z) - \delta\left(1 - F(z)\right) \int o_t(x) d\Psi_t(x) \\ -(1-\delta) \int_{\frac{z}{\gamma}}^{z} o_t(x) p_t(x) d\Psi_t(x) \\ - \int_0^z \left(1 - o_t(x)\right) q_t(\bar{x}, z) d\Psi_t(x)\end{aligned}$$

where $q_t(\bar{x}, z)$ is the average of the probabilities $q(x,z)$ taken over the all employers in $[0,z]$ and is given as:

$$q_t(\bar{x}, z) = \int_0^z o_t(s) q_t(x,s) \frac{l_t(s)}{\int l_t(z') d\Psi_t(z')} d\Psi_t(s)$$

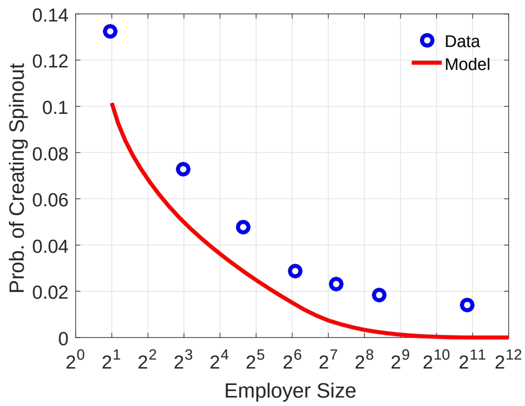
The equilibrium features a threshold productivity z^*, such that all agents with $z > z^*$ are entrepreneurs and the remainder are workers.

4 Calibration

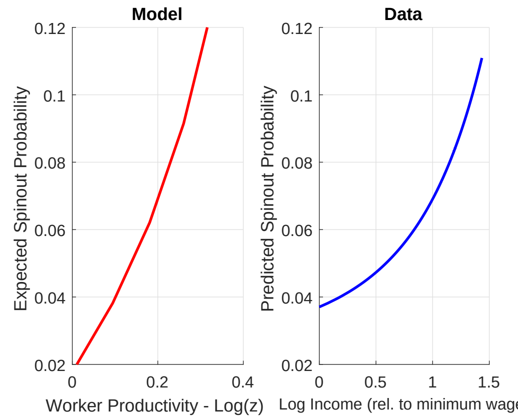
Aggregate productivity A and spinout efficiency M are normalized to 1 in Mexico. The learning cost function $c(\cdot)$ is assumed to be quadratic in the gap between worker and entrepreneur's productivity, that is, $\theta = 2$. With this assumption, the effort cost of employees to learn from employers is reminiscent of an adjustment cost that must be paid in order for employees to improve their productivity. We let the exogenous productivity distribution $F(z)$ be pareto with tail parameter $\lambda$and support on $(1, \infty)$. This leaves a total of nine parameters that need to be calibrated, five of which are chosen to match moments in the Mexican data while the remainder are taken directly from the data or literature.

The discount factor is set to $\beta = \frac{1}{1+0.06}$ and is chosen to target the 6% annual interest rate in Mexico[13]. The span of control parameter η is set to be 0.80 following Midrigan and Xu (2014). The parameters for the productivity investment cost function $i(z,q)$ are taken from Buera and Fattal-Jaef (2015) who choose $\phi = 10$ and $\mu = 4.8 \times 10^{-5}$. The convexity parameter ϕ is common for both worker productivity adoption and entrepreneurial productivity investment. There are four remaining parameters that must be set. These are, the scale parameter ν for the function $c(x,z,p)$, the pareto tail parameter λ for the exogenous distribution $F(z)$, the exogenous firm exit parameter δ and the productivity innovation step γ. These parameters are chosen to match,

[13]The annual interest rate is the long term government bond rate for 2015 and is significantly higher than the same rate (2%) observed in the US at that time. Studies in the literature typically target an annual interest rate of 4% and our results are robust to this assumption.



(a) Spinout Entry by Employer Size, Model and Data



(b) Spinout Entry by Worker productivity

Figure 7: Probability of Spinout Entry, Model and Data

respectively, the aggregate spinout rate, the share of entrepreneurs, spinout exit rate and the ratio of average spinout size at age 5 and 20. Table 5 lists these four parameters as well as the model's fit with the data for the targeted moments.

Table 5: Parameters Calibrated to Match Data Moments

Moment	Mexico Data	Model	Parameter
Aggregate Spinout Rate	0.067	0.062	$\nu = 0.107$
Average Spinout Size (Age 20)/(Age 5)	1.18	1.17	$\gamma = e^{0.06}$
Share of Entrepreneurs	0.19	0.18	$\lambda = 4.16$
Exit Rate in ENOE	0.28	0.29	$\delta = 0.36$

Notes: The aggregate spinout rate, share of entrepreneurs and exit rate is computed from the ENOE data. The ratio of spinout size at ages 5 and 20 is from the ENAMIN data. The exit rate is defined as the share of all entrepreneurs in year y that were no longer engaged in entrepreneurship in year $y+1$.

Figure 7a shows that the model fits well the observed negative relationship between employer size and the likelihood of spinout entry. The model also matches the positive relationship between worker productivity and probability of spinout entry as seen in figure 7b. The left panel plots the predicted probability of a worker forming a spinout which is obtained from a probit regression of log income on an indicator for spinout entry. The right panel shows the model predicted (average) probability of spinout entry by worker's productivity. Notice that in the model all worker's earn the same income; however, in the data, we interpret income in employment as a proxy for unobserved worker ability.

Finally, figure 8 compares the lifecycle employment dynamics of spinouts from the smallest relative to largest firms in the model and data. At entry, spinouts have the same productivity as their last employer. So, spinouts from large(small) firms start large(small). In the model, large

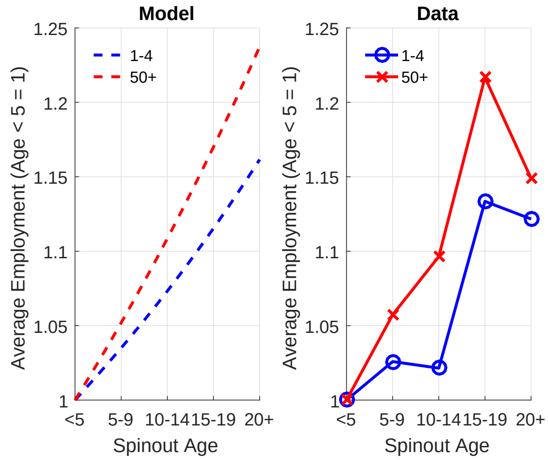


Figure 8: Average Number of Employees in the Data and Model

firms have greater incentives to innovate than small firms. This is intuitive since entrepreneurs closer to the margin have two ways, other than innovation, through which they can obtain higher productivity. First, given the thin right tail of the exogenous distribution, $F(z)$, small (low productivity) firms are more likely to receive a high idiosyncratic productivity draw than larger firms (with exogenous probability δ). Second, in the case that a low z draw induces exit, agents have the option to learn from and adopt their employer's productivity in the following periods. The option to learn in employment is particularly valuable to entrepreneurs near the margin since their future employer is likely to be far from the margin. Both these forces drive down the incentives for innovation for small firms. As a result, spinouts from smaller firms will start small and invest less in productivity improvements than spinouts from larger firms.[14] Given this intuition, the optimal investment probability $p^*(z)$ is weakly increasing in productivity.

5 Quantitative Analysis

In this section, we use the model to understand the forces that drive differences in aggregate outcomes, particularly, spinout formation between U.S. and Mexico. Before detailing the quantitative exercise, we briefly review the cross-country differences that will be targeted by the model. Figure 9 shows that for a given employer size, employees are less likely to form spinouts in the U.S. relative to Mexico. Taken together with the differences in the firm size distribution between the two economies, the U.S. has an aggregate spinout rate that is more than three times lower than the rate observed in Mexico (2.15% vs. 6.7%). Table 6 summarizes the outcomes that will be the focus of the quantitative exercise.

We first calibrate the aggregate productivity parameter A to match relative output per worker

[14] Since I focus on the stationary equilibrium, in the long run all firms will converge to the same firm size. The model size dynamics plotted in figure 8 are those obtained only from considering the equilibrium probability p of investment in productivity.

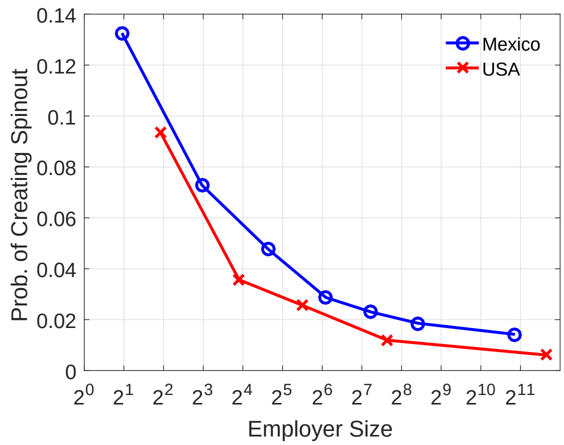


Figure 9: Probability of Entering Entrepreneurship, US and Mexico

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.

Table 6: Data Summary, USA and Mexico

	Mexico	US	Ratio
Aggregate Spinout Rate	0.067	0.022	0.32
Output per worker (thousands, 2010USD)	38	112	2.95
Avg. Firm Size (Age 16-20)/(Age<5)	1.19	2.22	1.87
Average Firm Size	10.7	21.8	2.04
Share of Entreprenuers	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. Economy wide average firm size is from Bento and Restuccia (2016). Share of entrepreneurs and exit rate is computed from the ENOE and CPS for Mexico and U.S. respectively.

between U.S. and Mexico. The calibration requires an almost three-fold difference in U.S. productivity relative to Mexico. The third column of table 7 reports the model's results from varying only A. Focusing first on the spinout rate, we find that aggregate productivity can account for only 29% of the gap in cross-country spinout rates.

As aggregate productivity increases, there are several forces that impact worker's incentives to learn from their employer and form spinouts. First, as the value in entrepreneurship increases, workers have greater incentive to form spinouts. On the other hand, the increased demand for labor increases wages which lowers incentives to adopt employer productivity. Finally, these forces shift the location of the marginal entrepreneur in the productivity distribution. This will directly influence the cost of productivity adoption as workers are now more likely to experience a wider gap between their own and their employer's productivity. As improvements in A resulted in a lower share of entrepreneurs and increased average firm size (relative to the benchmark Mexican economy) we know that the threshold for entry into entrepreneurship and subsequently the firm size distribution shift to the right. However, varying A leads to closing only 50% of the gap between Mexico and U.S. in both of these measures. Aggregate productivity leads to faster growth in firms over the lifecycle. This is due to the fact that adoption and innovation serve as substitutes in improving agent's productivity and as the incentives to learn in employment decline, agents switch to increased innovation.

In sum, while differences in aggregate productivity are shown to be important in the model with spinouts. They do not account for the gap in spinout formation between the two economies studied here. This motivates the need to consider other factors that influence spinout formation. A natural candidate is the efficiency with which workers learn from and adopt their employer's productivity, M. However, it's interpretation, in this context, requires clarification.

First, notice that changes in M act to scale the level of the cost paid by employees to learn from and adopt employer productivity. We interpret it as capturing a form of aggregate managerial quality in the economy. In particular, M represents managerial practices that pertain to the review and development of employees through performance monitoring. Effectively monitoring employee performance not only leads to higher firm productivity but it also ensures that employees are well-versed with the tasks required to operate the firm and more specifically complete the tasks required of them. As such, in economies with better performance monitoring, it should be easier for employees to learn from and adopt employer productivity. We consider these practices as distinct from those related to the operational management such as inventory control or production techniques. Indeed, operational practices are best captured in aggregate productivity term A as they relate only to firm productivity and not necessarily to employee performance. [15] With this interpretation in mind, the quantitative analysis distinguishes between

[15]The distinction between management practices that impact only the firm and those that impact both the firm and it's employees can be further clarified by referring to the World Management Survey (WMS) available at http://worldmanagementsurvey.org/ and it's measures cross-country differences in management quality. Of particular relevance are the measures of performance monitoring and talent management, which are interpreted as

those managerial practices that impact only existing entrepreneurs (A) and those that impact employees and subsequently future entrepreneurs (M).

Before discussing the calibration and results of varying M we briefly discuss the mechanisms by which it impacts spinout rate and aggregate outcomes. Firstly, data from the WMS indicates that average managerial quality is lower in Mexico relative to the U.S. (see for example Bloom and Van Reenen (2007)). This should be reflected in a lower value of M in the U.S. relative to Mexico, that is, it is easier for employees to adopt and learn from the employers. Given this lower cost of productivity adoption, it might seem counter-intuitive that making it easier to adopt employer productivity leads to *lower* spinout rates in the economy. Intuitively, this can be understood by noticing that the cheaper adoption of productivity from employers increases value in employment. This effect changes the occupational choice of agents with only the most productive agents entering entrepreneurship. Finally, while it is cheaper to adopt the productivity of employers as M decreases, this is offset by the increase in cost driven by changes in the occupational choice of agents and the resulting increase in productivity of the average employer.

This intuition is reflected in the fifth column of table 7 which reports aggregate outcomes when M is calibrated to match the spinout rate in U.S. As expected, the calibrated value of M is lower in the U.S. than in Mexico and explains around 12% of the observed differences in output per capita between U.S. and Mexico. The model also generates a lower level of entrepreneurship and higher level of average firm size relative to the benchmark. These changes are larger than those observed in the data. Finally, changes in M can explain 19% of the observed differences in firm dynamics.

Table 7: Aggregate Outcomes relative to Mexico benchmark

	Data	Model		
		$A = 2.9, M = 1$	$A = 1, M = \frac{1}{56}$	$A = 2.4, M = \frac{1}{10}$
Aggregate Spinout Rate	0.32	0.81	0.32*	0.32*
Output per worker	2.95	2.95*	1.24	2.95*
Average Firm Size	2.04	1.49	3.58	3.24
Share of Entreprenuers	0.44	0.72	0.32	0.35
Firm Size at age 20/age 5	1.87	1.08	1.17	1.26

Notes: The first column of the table show the ratio U.S. measures to those observed in Mexico. The remaining columns show the model implied ratios as parameter values change. * indicates those parameters that were targeted.

We conclude this section by studying the model outcomes generated by jointly calibrating aggregate productivity A and spinout formation efficiency M. These parameters are chosen to exactly match output per worker and spinout rates in the U.S., respectively. The last column of

captured in M and measures of operations management captured in A. The performance monitoring and talent management is 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 the adoption of modern production techniques and standardization of processes.

table 7 report the model predicted outcomes. Notice, that aggregate productivity gap A is lower than in the exercise when spinout efficiency remains fixed and vice-versa for M. This specification of the model can fully account for differences in the share of entrepreneurs and average firm size between US and Mexico. The model also more closely replicates the observed differences in firms dynamics, accounting for 30% of cross-country variation; which is larger than the share explained by either factor on it's own.

Overall, the quantitative analysis highlights the importance of considering spinout formation and it's determinants in driving aggregate outcomes. More specifically, management practices that impact employees play an important role in impacting not only incumbent firms but also future entrants.

6 Conclusion

This paper used detailed micro-data from Mexico to establish the relationship between employer size and spinout entry, size and growth. Novel to the literature on spinout performance is the finding that employer size is positively related to spinout size, not only at entry but also over the lifecycle - up to 20 years after entry.

Motivated by these empirical findings, we constructed a simple model of occupational choice which, when calibrated to match key moments of the Mexican economy, replicates the evidence uncovered. Employees enter as spinouts by learning from and adopting the productivity of their employers. The importance of spinout formation, for aggregate outcomes, is emphasized through the lens of the model. In particular, we tested the factors which drive differences in spinout entry between U.S. and Mexico. We found that aggregate productivity differences alone only account for 30% of these cross-country differences in spinout formation. Instead, an additional source of cross-country variation is introduced - the efficiency with which workers can learn from their employers. This factor affects aggregate outcomes through its impact on the value of being an employee. Differences in spinout formation efficiency account for 13% of the observed gap in output per worker and a larger share of differences in entrepreneurship, average firm size and dynamics than those from productivity alone. Interpreting this efficiency as reflecting managerial quality, these findings highlight the relevance of management practices not only through their impact on incumbent firms but also on future entrants - spinouts.

References

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 (2017): "Firm Entry and Exit and Aggregate Growth," Tech. rep., National Bureau of Economic Research.

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*.

BENTO, P. AND D. RESTUCCIA (2016): "Misallocation, Establishment Eize, and Productivity," .

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. S. KARLAN, AND A. SCHOAR (2013): "The impact of consulting services on small and medium enterprises: Evidence from a randomized trial in mexico," .

BUERA, F. AND R. FATTAL-JAEF (2015): "The dynamics of development: entrepreneurship, innovation, and reallocation," .

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.

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. 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.

HSIEH, C.-T. AND B. A. OLKEN (2014): “The missing "missing middle",” *The Journal of Economic Perspectives*, 28, 89–108.

LA PORTA, R. AND A. SHLEIFER (2014): “Informality and development,” *The Journal of Economic Perspectives*, 28, 109–126.

LUCAS JR, R. E. AND B. MOLL (2014): “Knowledge growth and the allocation of time,” *Journal of Political Economy*, 122, 1–51.

MIDRIGAN, V. AND D. Y. XU (2014): “Finance and misallocation: Evidence from plant-level data,” *The American Economic Review*, 104, 422–458.

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.

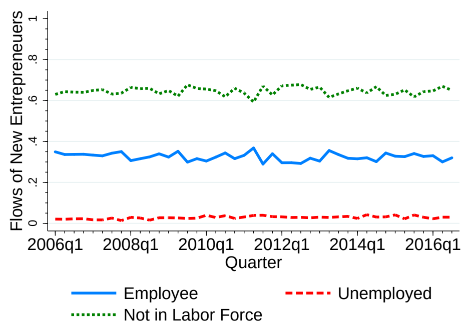
ROYS, N. AND A. SESHADRI (2013): “Economic development and the organization of production,” *Working Paper*.

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. We 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) Female

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.

A.1 shows that 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, we 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, we 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[16]. We 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 we study

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

spinout entry in the ENOE data[17]. 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 with lower levels.

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

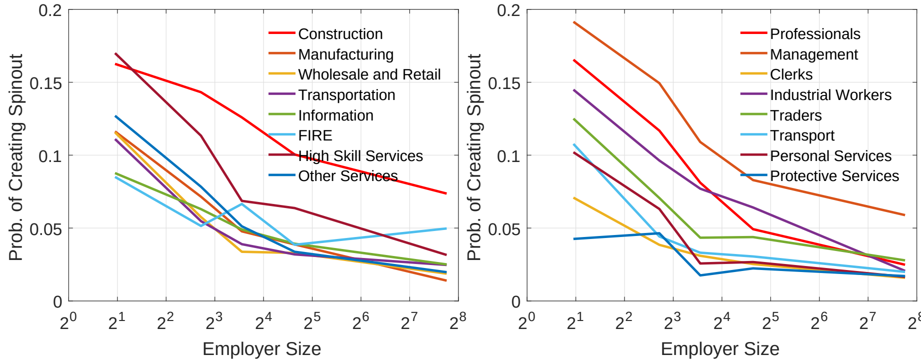
	(1) *Pr(Spinout)*	(2) *Pr(Spinout)*	(3) *Pr(Spinout)*
Employer Size:			
2 to 5	0.029***	0.035***	0.04***
	(0.001)	(0.001)	(0.002)
6 to 10	0.025***	0.027***	0.026***
	(0.001)	(0.001)	(0.003)
11 to 15	0.013***	0.014***	0.016***
	(0.001)	(0.002)	(0.003)
16 to 50	0.010***	0.010***	0.012***
	(0.000)	(0.001)	(0.002)
$Income_{emp}$ (Log, 2010MXN)	-	0.013***	0.012***
	-	(0.001)	(0.002)
Tenure (years)	-	-	0.001***
	-	-	(0.000)
Pseudo R^2	0.055	0.083	0.089
N	174,945	174,804	46,875

Notes: The omitted variable for employer size is the dummy for those employers with more than 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. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

We 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 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.

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

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



(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.

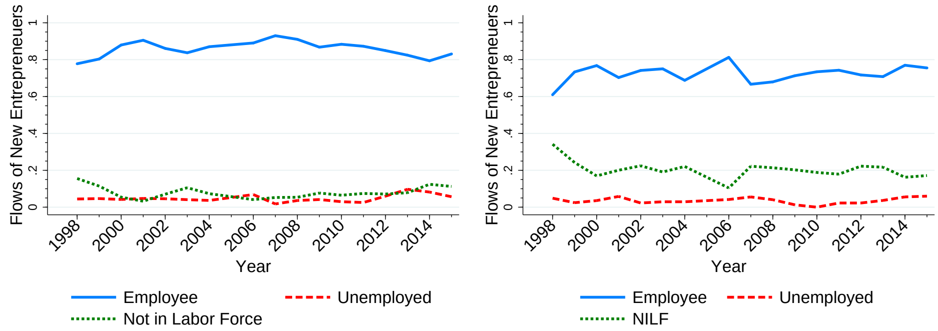
for starting their firm; i) *To earn higher income*, ii) *to pursue a good opportunity*, iii) *to pursue their career of choice*. Other possible motives include, to *supplement family income, only way to earn an income, required a more flexible schedule.*

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[18]. 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.3 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 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.

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



(a) Male　　(b) Female

Figure A.3: 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.

Spinout Entry Table A.2 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.2: 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

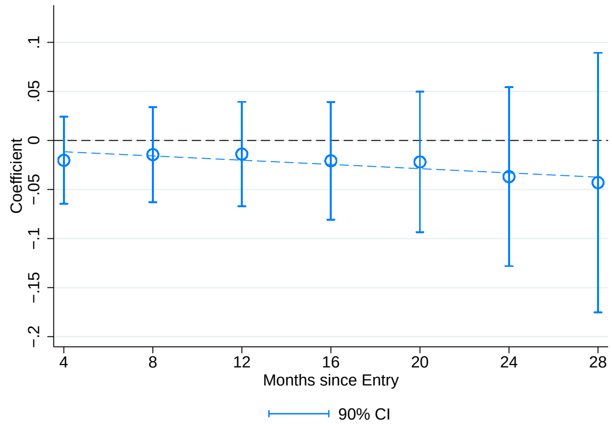


Figure A.4: Coefficient γ_t

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.

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 entry. However, there are several limitations to using the SIPP data for tracking spinout performance over the lifecycle which we 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, we consider only quarterly transitions. Furthermore, given the attrition in the SIPP we restrict the sample to include those individuals for whom we have at least 8 months of information [19].

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 [20]. 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 we expect $\gamma_t < 0$ for all t and also that $\gamma_{t+1} < \gamma_t$. Figure A.4 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

[19]After making these restrictions, we are left with a sample of 24,799 monthly observations from 909 individuals who form spinouts.

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

this data less than ideal to study spinout performance by employer size and can explain the large confidence intervals in figure A.4.

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.5 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.

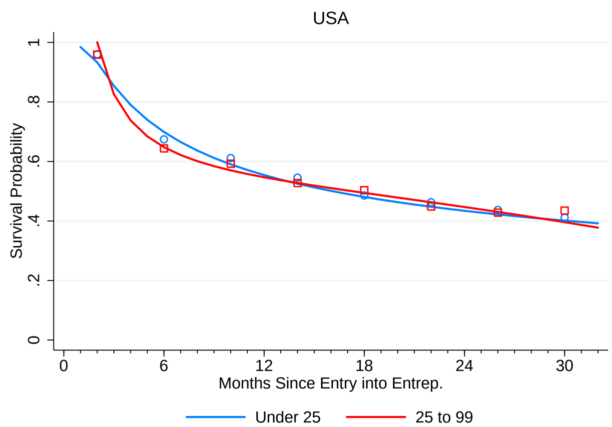


Figure A.5: Probability of Exit

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.