Entrepreneurial Spillovers Across Coworkers*

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Abstract

Using large-scale administrative data, I track the employment and entrepreneurship of over forty million Americans and investigate entrepreneurial spillovers across coworkers, based on the idea that individuals who start their own firms learn institutional knowledge and entrepreneurial skills that they may teach others. I find that an individual whose current coworkers have more prior entrepreneurship experience is more likely to become an entrepreneur themself within the next five years, and these spillovers are strongest among workers with similar jobs and demographics. Furthermore, an individual is more likely to become a successful entrepreneur if those coworkers were themselves successful entrepreneurs. To quantify the role of these spillovers, I build a structural model of entrepreneurship and learning and estimate that the aggregate entrepreneurship rate would be 10% lower in the absence of learning.

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Prior economic research has documented the presence of entrepreneurial spillovers but has found mixed evidence on *what* is transmitted in these spillovers. Some spillovers appear to encourage more entrepreneurship without increasing productivity, effectively lowering the entry cost to entrepreneurship: Nanda and Sørensen (2010) argue that working with entrepreneurial coworkers can motivate or inspire a worker to become an entrepreneur themself. Other spillovers both promote entrepreneurship *and* make subsequent entrepreneurs more successful: Guiso, Pistaferri, and Schivardi (2020) argue that exposure to more firms leads individuals to accrue more entrepreneurial skills, such as the ability to better manage a firm. Meanwhile, other spillovers actually appear to discourage entrepreneurship: Lerner and Malmendier (2013) find evidence of entrepreneurial peers dissuading ventures that are unlikely to succeed. Because young firms play disproportionate roles in driving aggregate employment (Decker et al. (2014)) and productivity (Klenow and Li (2021)) growth, entrepreneurial spillovers have the potential to affect the aggregate economy, but how they do so depends on which type of spillover is dominant in the aggregate.

The lack of consensus on the mechanisms of entrepreneurial spillovers in part arises because context likely matters. For instance, Lerner and Malmendier (2013) study spillovers across quasi-randomly assigned Harvard MBA classmates; while this setting yields identification of causal spillovers, the specificity of the context makes the results difficult to extrapolate to general settings. Taken together, the literature suggests that the mechanisms of spillovers are multidimensional, but it is difficult to discern the relative importance of the mechanisms in the aggregate without studying a broad context.

This paper presents new evidence on the mechanisms and implications of entrepreneurial spillovers in a broad and relevant context: coworker relationships in the United States. I present empirical evidence of individuals experiencing two types of spillovers from their coworkers who were recently entrepreneurs. First, there are spillovers that decrease the entry cost to entrepreneurship, for instance by transmitting institutional knowledge; these spillovers push individuals who work with more former entrepreneurs towards entrepreneurship without improving productivity. Second, there are spillovers that increase the productivity of firms, perhaps by transmitting entrepreneurial skills; these spillovers also push individuals who work with more *productive* former entrepreneurs towards entrepreneurship but additionally improve productivity. Both types of spillovers are relevant in the national context: using a structural model, I estimate that these spillovers on net increase aggregate firm entry by 10% on average across twenty years.

Using the Longitudinal Employer-Household Dynamics (LEHD) data and additional data on firms from the U.S. Census Bureau, I combine longitudinal information on individuals and their coworkers with data on firms' outcomes in order to quantify the two types of entrepreneurial spillovers. The scope of this data, which is large and spans many states and industries, allows me to explore the heterogeneity of these spillovers and to construct estimates that are relevant in the national context. Furthermore, studying the characteristics of the firms that arise through these spillovers allows me both to evaluate the productivity implications of these spillovers and to characterize the lessons learned through these spillovers. While there are several ways of measuring entrepreneurship, I predominantly follow the recent literature and call an individual an entrepreneur if they are one of the top three earners at a new firm (Agarwal et al. (2016), Kerr and Kerr (2017), and Azoulay et al. (2018)). This measure of entrepreneurship captures individuals who likely hold influential positions at young firms.

In the first part of the paper, I estimate entrepreneurial spillovers across establishment coworkers by leveraging variation in individuals' exposure to coworkers with prior (within the past five years) entrepreneurial experience. Empirically, some individuals work with more former entrepreneurs, and these former entrepreneurs vary in terms of how productive their firms were. These two sources of variation allow me to explore whether more exposure, both in general and to more productive entrepreneurs, predicts more future entrepreneurship (the extensive margin) and, for individuals who subsequently become entrepreneurs, different firm outcomes (the intensive margin).

Studying both extensive and intensive margin spillovers sheds light on the mechanisms of the spillovers and allows me to quantify how these spillovers affect aggregate outcomes. Broadly speaking, the extensive margin tells us about the presence of spillovers: if individuals who work with more entrepreneurial coworkers are more likely to become entrepreneurs themselves, then *something* is transmitted from the coworkers.

Meanwhile, the intensive margin contains information on whether these spillovers lower entry costs (e.g., transmit institutional knowledge, such as how to register a business or choose a legal structure) or increase productivity (e.g., transmit entrepreneurial skills, such has how to build a strong business plan and hire productive workers). On the one hand, if more exposed individuals tend to start less successful firms, such that the marginal entrepreneur is less productive, this means that the exposure pushed some less productive individuals to become entrepreneurs (e.g., by lowering the entry cost). On the other hand, if more exposed individuals tend to start more productive firms, this means that either prior entrepreneurs discouraged unproductive entrepreneurs from starting a business or that exposure actually increased individuals' productivity as entrepreneurs (e.g., by transmitting good advice).

In my extensive margin analysis, I estimate regression models of whether individuals who work with more former entrepreneurs in 2004 are more likely to become entrepreneurs themselves subsequently, between 2005 and 2009. I find evidence of positive spillovers: individuals who work with one standard deviation (about 10 percentage points) higher share of coworkers who were entrepreneurs in the past five years are 8% more likely to become entrepreneurs themselves in the next five years, relative to the average likelihood. Through a back-of-the-envelope calculation, this pattern suggests that spillovers generate an additional 3% of entrepreneurs in the aggregate.

While the average extensive margin spillover is large (8%, relative of the mean), there is substantial heterogeneity. The spillovers tend to be amplified by exposure to relatively more successful entrepreneurial coworkers (i.e., entrepreneurs whose firms were relatively large or productive). While spillovers exist in most sectors, they are largest in the accommodation and food service sector, suggesting that the aggregate evidence of spillovers are not driven by the "high tech" sector that previous literature has studied (Kerr and Kominers (2015)). Additionally, these spillovers are stronger for younger individuals and do not exist for near-retirement individuals, with individuals "learning" the most from their relatively older coworkers. The spillovers are strongest across coworkers who may be more likely to regularly interact in the workplace or to form mentorship relationships, namely coworkers who earn similar wages or who are of the same sex or immigration status. Finally, spillovers generate new entrepreneurs: individuals who themselves have recent entrepreneurial experience are not more likely to become entrepreneurs after working with more entrepreneurial coworkers, consistent with these individuals having had their own experiences and thus little to learn from entrepreneurial coworkers.

In my intensive margin analysis, I study the entrepreneurial outcomes of the individuals who become entrepreneurs between 2005 and 2009 and find evidence of both spillovers of institutional knowledge and entrepreneurial skill. I estimate regressions models of whether an individual's future entrepreneurial firm's characteristics vary if they were exposed to more entrepreneurial coworkers in 2004. I find that individuals who work with more entrepreneurial coworkers tend to start firms that are smaller in both employment and sales and are less likely to survive, consistent with a net pattern of individuals on average simply being inspired or learning the institutional knowledge needed to start a firm, as this leads to less productive individuals choosing to become entrepreneurs. However, if the individuals' entrepreneurial coworkers ran larger or longer-surviving firms, the individuals are more likely to start firms that are larger and more likely to survive. These results suggest scope for *some* true productivity gains via entrepreneurial skill spillovers, if the spillovers are from particularly successful entrepreneurs.

Coworkers are not randomly assigned to individuals, creating identification concerns, despite the rich set of controls included in the baseline specifications. For instance, entrepreneurship-prone individuals may cluster at firms or establishments for a variety or reasons not captured by the observable controls, such that the spillovers I measure may not be evidence of learning from coworkers. Instead, these spillovers may reflect firm or establishment effects, consistent with the literature of entrepreneurs "spawning" from their employers. Or, these spillovers may reflect pure spurious correlation, if these entrepreneurship-prone individuals work at firms for reasons entirely unrelated to entrepreneurship, for instance if they are also more educated. Additionally, individuals living and working in particular locations or industries may experience common business shocks that make entrepreneurship more or less attractive.

I address these identification concerns through several robustness analyses. First, I show that these spillovers do not reflect entrepreneurial individuals simply clustering at certain firms or establishments. Instead, individuals disproportionately appear to learn from their true coworkers — other workers at their establishment — as opposed to other workers at the same firm but at other establishments or workers who work at the same establishment either before they joined or after they leave. Second, I show that these spillovers cannot be fully accounted for by selection into having specific coworkers; the results are not driven by individuals seeking out entrepreneurial coworkers. Instead, spillovers are also apparent from coworkers who joined an individual's establishment after they joined, whom the individual should not have been able to select on when choosing to join the firm. Finally, spillovers are not driven by local or industry common shocks, as the patterns persist with the inclusion of additional location and industry fixed effects.

To further bolster a causal interpretation of the spillovers, I present direct survey evidence of entrepreneurial spillovers across coworkers. By linking individuals who become entrepreneurs to firm owners in a Census survey, I analyze reported motivations for these individuals' entrepreneurship. I find that the individuals who previously worked with more former entrepreneurs are more likely to report that they had an entrepreneurial role model who led them to start a firm. In other words, the individuals who I predict become entrepreneurs *because* of their exposure to entrepreneurial coworkers are more likely to report having an entrepreneurial role model, consistent with these spillovers actually existing.

I also present evidence against several alternative mechanisms through which exposure to entrepreneurial spillovers may convey something beyond institutional knowledge and entrepreneurial skills. I document that the spillovers are not driven by entrepreneurial coworkers taking individuals along with them for their next venture, teaching generic leadership skills, or providing direct funding or access to financial networks.

Taken together, the extensive and intensive margin results highlight the multidimensional nature of entrepreneurial spillovers, yet quantifying the importance of these spillovers in the aggregate is difficult to do without adding more structure. If we want to know how these spillovers affect the aggregate entrepreneurship rate, or how much these spillovers would propagate the effects of policies subsidizing entrepreneurship, we need to estimate counterfactuals, which require a model.

To quantify the role of the entrepreneurial spillovers, in the final part of the paper I build and estimate a structural model of entrepreneurial spillovers. I extend the canonical Lucas (1978) occupational choice model in which individuals choose between wage work and entrepreneurship. In my model, I incorporate entrepreneurial spillovers across randomly-assigned coworkers. In line with the reduced form results, I include two types of spillovers: spillovers that lower the costs to entrepreneurship and spillovers that increase the productivity of entrepreneurs.

I estimate this model using the Simulated Method of Moments (SMM), targeting empirical moments of earnings, firm characteristics (namely payroll, which increases with productivity in the model), and entrepreneurship. Given the estimation, I quantify how entrepreneurial spillovers promote aggregate entrepreneurship by conducting counterfactual analyses in which I remove learning from coworkers. I estimate that, in the absence of learning, entrepreneurship would be 10% lower, on average across 1994 through 2013, with the majority of this difference being driven by spillovers that increase the productivity of entrepreneurs. However, the spillovers that increase productivity do not dramatically increase aggregate productivity, likely because these spillovers prompt some otherwise-low productivity individuals to choose entrepreneurship. Furthermore, because these estimates mean that spillovers increase entrepreneurship, they moderate the secular decline in entrepreneurship: in the absence of learning, entrepreneurship decreases more in response to rising average costs and falling average productivity. These estimates suggest that entrepreneurial spillovers play non-negligible roles in determining aggregate patterns.

This paper contributes to several literatures. First, it contributes to the literature on entrepreneurial occupation choice. There is a plethora of reasons for which an individual may choose to start their own firm, from coming up with a good idea, to having the access to resources needed to start a firm, to simply wanting to be their own boss or being risk-loving or tolerant. With these many reasons, there is a very large literature on entrepreneurship motivation. See Segal, Borgia, and Schoenfeld (2005) for a broad description of the various motivations.[1] My paper contributes by analyzing an understudied dimension — learning from entrepreneurs — using high quality large-scale data.

Second, the paper relates to papers on learning entrepreneurship from coworkers and communities.[2] The single closest paper to mine is Nanda and Sørensen (2010), which estimates entrepreneurial spillovers across coworkers in Denmark, finding evidence of positive extensive margin spillovers in support of learning, but notably does not study the characteristics of the subsequent firms.[3] Beyond entrepreneurial learning across coworkers, other work considers spillovers in terms of entrepreneurship in other contexts. Guiso, Pistaferri, and Schivardi (2020) and Giannetti and Simonov (2009), for instance, find evidence of individuals learning entrepreneurship from their broader (geographic) community. Meanwhile, Lerner and Malmendier (2013) provide some of the best-identified evidence of entrepreneurial spillovers by leveraging randomly assigned peer groups among MBAs and find evidence of nuanced entrepreneurial spillovers; having more previous entrepreneur classmates reduced students' likelihood of later becoming an entrepreneur, driven by a decrease

[1] There is a related literature on the innovative and corporate motivations and decisions of firm managers and executives. See, for example, Bertrand and Schoar (2003), Graham et al. (2009), Campbell et al. (2011), Malmendier, Tate, and Yan (2011), Hirshleifer, Low, and Teoh (2012), Kaplan, Klebanov, and Sorensen (2012), Ben-David, Graham, and Harvey (2013), Graham, Harvey, and Puri (2013), Faleye, Kovacs, and Venkateswaran (2014), and Hall et al. (2014).

[2] There is also evidence of entrepreneurial spillovers within family members (e.g., Hvide and Oyer (2018), Akcigit et al. (2021), Lindquist, Sol, and Van Praag (2015), and Djankov et al. (2006)) as well as from employer to worker (e.g., Gompers, Lerner, and Scharfstein (2005) and Bosma et al. (2012)). Additionally, there is mixed evidence of peer effects in the context of formal entrepreneurial training (e.g., Chatterji et al. (2019), Hasan and Koning (2019), Field et al. (2016), Karlan and Valdivia (2011)). More broadly, there is evidence of peer and network effects across firms, executives, and individuals in terms of executive compensation and financial decisions; see, for example, Davis and Greve (1997), Hong, Kubik, and Stein (2005), Cohen, Frazzini, and Malloy (2008), Shue (2013), Bursztyn et al. (2014), Leary and Roberts (2014), Fracassi (2017). and Bernstein et al. (2019).

[3] Nanda and Sørensen (2010) find that a one standard deviation higher exposure to entrepreneurial coworkers predicts a 4% higher likelihood of becoming an entrepreneur subsequently. Surveying 292 representative Dutch entrepreneurs, Bosma et al. (2012) present evidence of former colleagues and employers serving as role models for entrepreneurship. Stuart and Ding (2006) find evidence of academic life scientists' entrepreneurship being positively correlated with their colleagues' experience with commercial science.

in future unsuccessful entrepreneurship.[4]

I complement these papers' findings by using much larger, broader data that allow me to study a wide span of the American workforce and to explore heterogeneity and the mechanisms through which the spillovers operate. Through this process, I am able both to measure spillovers in a general setting and to evaluate the types of firms that emerge from these spillovers. I also provide evidence that context matters; in Section A.IV, I identify coworkers similar to the MBAs in Lerner and Malmendier (2013), for whom I find evidence consistent with that paper's findings, with these like-MBA entrepreneurial coworkers appearing to dissuade unsuccessful entrepreneurship. This comparison both supports the causal interpretation of my paper's spillovers, since my findings for this particular group are consistent with those from a setting with exogenous variation in exposure to former entrepreneurs, and suggests that my estimates may better capture the experience of the average American worker.

Finally, this paper contributes to the broader literature on growth driven by new firms, their employees, and declining dynamism. Decker et al. (2014) documents a decline in firm and labor dynamism over the past few decades, with an increasing pace of decline after 2000, and suggest that this pattern may reflect a concerning decline in entrepreneurship.[5] Haltiwanger, Jarmin, and Miranda (2013) argue that, contrary to public opinion at the time, young firms, rather than necessarily small ones, drive growth by growing quickly. More recently, Klenow and Li (2021) argue that young firms contribute disproportionately to the level of growth (but not necessarily as much to the changing growth rate). However, as Botelho, Fehder, and Hochberg (2021) summarize, young firms are not a monolith: a small innovative subset of young firms account for much of the growth-promoting role of entrepreneurship. The employees, particularly the first ones, of these young firms may be particularly important to growth, as Choi et al. (2019) argue that initial employees are instrumental to new firms' performance. I complement this literature by investigating how these spillovers, in the presence of declining entrepreneurship rates, matter for aggregate growth.

The remainder of this paper is organized as follows. Section I describes the U.S. Census Bureau data and samples used in both the reduced form and the model analyses. Section II presents a brief conceptual framework, demonstrating both why spillovers may be multidimensional and how the extensive and intensive margin analyses speak to the dimensions. Section III describes and presents the results of the extensive margin analysis, while Section IV follows with the intensive margin analysis. Section V presents the structural model of entrepreneurial spillovers. Section VI concludes.

I Data

I use several datasets from the U.S. Census Bureau to measure the entrepreneurship and entrepreneurial outcomes for individuals and their coworkers. See Section A.I for details on these datasets and how samples and variables are constructed. Here, I present broad summary statistics for the main sample, highlighting that entrepreneurs are quite different from average workers.

[4] Shue (2013) and Hacamo and Kleiner (2020a) also study entrepreneurial spillovers across MBA classmates, finding evidence of positive spillovers in terms of firm policies and confidence, respectively. For younger students, Falck, Heblich, and Luedemann (2012) find positive correlations between a teenager's entrepreneurial intentions and their classmates'.

[5] The reason(s) for the decline in entrepreneurship are uncertain. For example, Karahan, Pugsley, and Şahin (2019), among others, argue that decline is driven by population aging. Salgado (2020) argues that increases in returns to high-skill labor, through skill-biased technical change and decreases in the price of capital, account for three-quarters of the decline.

I.1 Coworkers and firm and worker characteristics

I measure earnings, demographics, and firm information for individuals and their coworkers using the Longitudinal Employer Household Dynamics (LEHD), which is the matched employer-employee data that covers the near-universe of formally employed workers in the United States. Here, I provide basic information on the LEHD.

The LEHD is constructed from firm-side state unemployment insurance (UI) records and contains information on employment, earnings, and demographics, with longitudinal employer and individual identifiers that allow me to link individuals and their coworkers and follow workers over time. I use LEHD data from 1993 to 2013 for a balanced sample of 18 states.[6]

I study each individual's employer (and coworkers) at two levels of aggregation: the **establishment** and the **firm**. For this paper, the "establishment" is the least aggregate firm unit available in the LEHD, i.e., a state-level unemployment insurance account (called a State Employer Identification Number, or SEIN). For many employers, the establishment has a single location; for others, the establishment is a pooled collection of physical locations within a given state, generally within a single sector. Approximately half of individuals work at single-location establishments in 2004. The "firm" (given by the Census FIRMID) pools all of these establishments for a firm, across states and sectors.

For each individual, I identify their highest paying firm in each year, call this their "primary firm," and only consider their earnings at that firm in a given year. Within that firm, I call the individual's highest paying establishment their "primary establishment," I subsequently call other workers with the same primary establishment (or firm) the individual's **coworkers**.

In my empirical analyses, I control for and analyze heterogeneity along several base characteristics from the LEHD. These characteristics include individuals' firm-level earnings, deflated to 2010 dollars and which include salaries and wages as well as bonuses, stock options, and other cash pay, as well as their demographics, including age, sex, race/ethnicity, education, and country of birth. Additionally, these characteristics include establishment and firm variables, including industry and sector (based on 6-digit NAICS codes) and employment (counting the individual and their coworkers).

I.2 Entrepreneurship and entrepreneurial outcomes

I measure entrepreneurship for individuals and their coworkers using the LEHD, which I supplement with firm entry information from the Longitudinal Business Database (LBD), which tracks all U.S. firms with paid employees over time. While there are several ways of measuring entrepreneurship, I follow the recent literature[7] and call an individual an **entrepreneur** if they are a top three earner at a new firm; specifically, I identify the three highest annual earners at a firm in the first year in which it employs workers. This measure of entrepreneurship captures individuals who likely hold influential positions at young firms.

For entrepreneurs, I measure a variety of outcomes for their entrepreneurial firms using the LEHD and several other Census data products. These outcomes include size and survival from the LEHD, revenue and revenue productivity from the LBD, and a variety of entrepreneurial outcomes from the Annual Survey of Entrepreneurs (ASE). As discussed in Section A.I, I additionally use management information from the

[6]This results in a balanced panel of the following 18 states: AK, AZ, CA, CO, FL, ID, IL, IN, KS, LA, MD, MO MT, NC, OR, WA, WI, WY (other states only provide data starting in later years). In the 2004 Current Population Survey Annual Social and Economic Supplement (CPS ASEC), these 18 states account for 44% of age 20-64 national employment. I source CPS data from IPUMS (Flood et al. (2020)).

[7]I follow Agarwal et al. (2016), Kerr and Kerr (2017), and Azoulay et al. (2018) in doing this; Azoulay et al. (2018) audits this initial team definition using W-2 records to compare founders to initial team members. They find that "90% of the owner-workers are in fact among the top three earners in the firm during the first year," though this coverage is noisy.

Management and Organizational Practices Survey (MOPS), legal form from the Business Register (BR), and whether a firm is privately-held or publicly-traded from the Compustat-SSEL Bridge (CSB).

Size, revenue productivity, and survival I measure *absolute* firm size in terms of employment and payroll from the LEHD and revenue from the LBD, which contains firm-level information on national revenue and employment starting in 1997 (Haltiwanger et al. (2017)). Additionally, based on the LBD information on revenue and employment, I construct revenue productivity (i.e., log(revenue/employment)).[8] I also measure *relative* firm size and revenue productivity by identifying firms whose size or revenue productivity falls in the top 10% among firms that enter in the same year and (6-digit NAICS) industry. I measure a firm's survival to a given age by whether the firm has nonzero LEHD employment at that age; note that I call a firm's age 1 in its entry year and increment each year afterwards.

Reason for starting a business I consider survey evidence of why entrepreneurs start businesses using information from the 2014-2016 Annual Survey of Entrepreneurs (ASE), which collects information from owners of a representative sample of non-farm firms with paid employees and receipts of at least $1,000. For each firm owner, the ASE asks why they became an entrepreneur. As described in detail in Sections III.3 and A.I, I match entrepreneurs in the LEHD to owners of their entrepreneurial firm in the ASE based on demographics and use this question to measure how important entrepreneurial friends or family members were as role models for the owner's entrepreneurship.

I.3 Samples

I use several samples throughout this paper. I use data from 1994 to 2013 to describe aggregate patterns and to estimate my model. For the reduced form analyses, my primary sample contains individuals with coworkers in 2004 for whom I can measure previous and future entrepreneurial outcomes. For my analysis of outcomes from the ASE and MOPS, which are measured after 2010, I focus on later samples.

I.4 Summary statistics

Entrepreneurship experience and success is not randomly allocated across individuals in the economy. Rather, individuals who become entrepreneurs are different along several dimensions. Furthermore, individuals' entrepreneurial coworkers started firms of varying success in the past. Here, I present summary statistics that motivate the empirical strategy in the remainder of the paper.

Workers vs. entrepreneurs Entrepreneurs are quite different from the general labor force. Yet, entrepreneurs work and start firms in all sectors of the economy, making the potential scope of entrepreneurial spillovers large.

For the 2004 sample, in Table 1 I present entrepreneurial, demographic, job, and establishment characteristics of all individuals in 2004 and of those who become entrepreneurs between 2005 and 2009. Relative to the general population, future entrepreneurs tend to be young, male, educated, White and Asian, born outside the U.S., higher earning, and working at smaller, younger firms. They also tend to work with more entrepreneurial coworkers, which I explore more systematically in the remainder of the paper.

For one heterogeneity analysis below, it is worth noting here that is a non-monotonic relationship between entrepreneurship and age, recently documented in Azoulay et al. (2018). While entrepreneurs tend to be younger than workers, there is a distinct inverse-U relationship between age and entrepreneurship, as shown

[8] Note that revenue productivity is a distinct concept from "productivity" discussed elsewhere in the paper, including the model.

in Figure 1. Entrepreneurship rates by age peak around age 35, with the share of individuals aged 35 who are entrepreneurs being nearly double that of individuals aged 20 or 70.

Despite the fact that future entrepreneurs are different from workers in general, they work and become entrepreneurs across the economy. Figure 2 shows the sectoral composition of all individuals and future entrepreneurs, plotting the shares of all individuals compared to the shares of future entrepreneurs employed in each 2004 primary firm sector (based on NAICS codes), along with the share of future entrepreneurs' firms' entry year sectors. As the figure shows, future entrepreneurs work in all industries in 2004 and start firms in all industries, though they disproportionately work and start firms in construction, professional/scientific/technical services (e.g., R&D and law and accounting services), and accommodation and food services, and less often appear in manufacturing and health, compared to the general workforce. Nearly half of future entrepreneurs start firms in the same sector as their 2004 establishment.

Entrepreneurial coworkers It is additionally important to note that coworkers with recent entrepreneurial experience were not necessarily the most productive entrepreneurs: indeed, many of their firms no longer exist, and they are now primarily employed at a different firm. As discussed below, this likely shapes the lessons that these coworkers can teach.

Table 2 documents summary statistics on the firm outcomes for coworkers and individuals who were entrepreneurs within the previous five years (1999-2003). The table shows the outcomes both in terms of the average coworkers (columns 1 and 2, i.e., average outcomes for coworkers who were previous entrepreneurs) and at the individual level (columns 3 and 4, i.e., average outcomes for individuals who were previous entrepreneurs). For this paper, the past outcomes of the average set of entrepreneurial coworkers (columns 1 and 2) describe the average "treatment" that individuals face in the workforce. The average past outcomes of previous entrepreneurs in general (columns 3 and 4, many of whom started their current firm) provide benchmarks for the success of the average set of entrepreneurial coworkers.

Table 2 highlights that entrepreneurial coworkers generally started relatively unsuccessful (i.e., shorter-surviving, smaller, and less productive) firms, although some were relatively successful. Less than half of individuals' entrepreneurial coworkers started firms that survive to age 5, on average, while over 60% of all recent entrepreneurs' firms survive that long. Alongside these higher exit rates, many entrepreneurial coworkers have since returned to being a standard worker: while around 52% of the recent entrepreneurs in general started their current firms, less than 9% of an individual's entrepreneurial coworkers are entrepreneurs of the current firm, on average. This means that many of these entrepreneurial coworkers have left the firm they started and now work at someone else's firm.[9] Yet, some entrepreneurial coworkers started relatively successful firms; for instance, on average 15% of entrepreneurial coworkers started firms that were in the top 10% of entry year log employment, amongst firms that started in the same year and industry as them.

Taken together, these summary statistics suggest that exposure to entrepreneurial coworkers is likely quite different from, e.g., mentorship through start-up accelerator programs: the average entrepreneurial coworker did not start a hyper-productive firm.[10] However, the fact that there is heterogeneity in these entrepreneurial coworkers' outcomes — some individuals get "lucky" and work with successful former entrepreneurs — allows me to explore the roles of both exposure to *more* entrepreneurs and to *more successful* entrepreneurs in

[9]It is important to note that an entrepreneur leaving their entrepreneurial firm need not indicate that the firm is unsuccessful. Rather, firm founders frequently are replaced by more professional CEOs (sometimes willingly, sometimes not; see Kaehr Serra and Thiel (2019)). Venture-capital backed companies tend to aggressively replace founders with outside CEOs, such that these shifts can actually indicate firm growth (Hellmann and Puri (2002)).

[10]Note that entrepreneurs of failed firms need not be discouraged from entrepreneurship themselves, and consequently they need not discourage others. As Dillon and Stanton (2017) document, serial entrepreneurs frequently "dip in and out" of standard wage work.

Sections III and IV below.

II Conceptual framework: Multidimensional spillovers

When an individual works with former entrepreneurs, they may experience multiple dimensions of entrepreneurial spillovers, and the ultimate implications of these spillovers depend on *what* these coworkers can teach them. Here, I present a conceptual framework in which individuals may learn from former entrepreneurs both how to be more **productive** entrepreneurs, e.g., by learning entrepreneurial skills, and to have lower **entrepreneurial costs**, e.g., by learning institutional knowledge. On the margin, both of these types of spillovers encourage more entrepreneurship (i.e., have positive *extensive margin* effects), but only productivity spillovers lead to productivity gains (i.e., have positive *intensive margin* effects).

These patterns mean that I can empirically measure the presence of entrepreneurial spillovers by studying the extensive margin, leveraging variation in exposure to entrepreneurial coworkers (Section III). Then, I can disentangle the relative strengths of the spillovers to productivity and cost by studying the intensive margin, leveraging variation in exposure to *productive* entrepreneurial coworkers (Section IV).

II.1 Individuals choose between wage work and entrepreneurship

To see how studying both extensive and intensive margin spillovers is informative about *what* is transmitted across coworkers, consider a version of the occupational choice model of Lucas (1978), which I extend in Section V.[11]

Suppose a positive mass of individuals maximize utility by choosing between wage work and entrepreneurship, given an equilibrium wage w. Let individuals be heterogeneous along two dimensions: how productive they would be as an entrepreneur (given by productivity z) and how costly entrepreneurship is to them (given by fixed cost c). (Note that productivity z is a distinct concept from, and will not be mapped to, revenue productivity defined in Section I.)

Formally, individuals choose between work and entrepreneurship by maximizing

$$V(z,c;w) = \max_{x\in\{0,1\}} \Big\{ \underbrace{(1-x)w}_{\text{worker}} + \underbrace{x \max_{N}(f(z,N) - wN - c)}_{\text{entrepreneur}} \Big\}. \tag{1}$$

Each individual chooses between wage work ($x = 0$), in which case they earn the equilibrium wage, or entrepreneurship ($x = 1$), in which case they earn a profit after optimizing their labor demand (i.e., optimal N), producing (where $f(z, N)$ increases in both inputs), and paying wages and the fixed cost. In equilibrium, the wage clears the labor market: given the equilibrium wage, the number of workers (labor supply) equals the total labor demand from entrepreneurs, with all individuals optimally choosing between work and entrepreneurship (see Section V for full details).

Individuals will opt for entrepreneurship if their payoff as an entrepreneur exceeds their payoff as a worker. An entrepreneur's productivity z increases their payoff as an entrepreneur, while their cost c decreases it. Conceptually, z captures an entrepreneur's ability to extract more profits from a given level of labor, which empirically might derive from a new entrepreneur's skills in conducting market research, producing initial

[11] This conceptual framework is similar to that in Guiso, Pistaferri, and Schivardi (2020), who in turn follow Guiso and Schivardi (2011) and Lucas (1978). Note that Guiso, Pistaferri, and Schivardi (2020) also include physical capital, but this does not affect the intuition.

products and services, and hiring and managing productive workers.[12] Meanwhile, c captures the fixed costs to entrepreneurship, which for new entrepreneurs may include overhead costs as well as logistical necessities, such as choosing the optimal legal structure and banking relationships for a firm as well as correctly obtaining and maintaining tax IDs, licenses, and permits.[13]

The solution to this model has a simple cutoff property: for any given level of c, there is a threshold level of z above which individuals choose to become entrepreneurs, given the wage. In other words, conditional on the fixed cost, individuals with a "high enough" productivity opt into entrepreneurship. This threshold, $z^*(c)$, is defined as the productivity at which an individual is indifferent between wage work and entrepreneurship, given the wage and cost c. Denoting $\pi(\cdot)$ as profits, given optimal labor demand and the wage (excluding the fixed cost), this threshold is such that[14]

$$w = \max_N (f(z^*(c), N) - wN - c) = \pi(z^*(c); w) - c. \tag{2}$$

The threshold $z^*(c)$ increases in c: as entrepreneurship becomes more costly, only the relatively more productive individuals will choose entrepreneurship.[15] This means that, all else equal, raising the fixed cost to entrepreneurship translates to a higher productivity of the marginal entrepreneur:

$$\frac{\partial z^*(c)}{\partial c} > 0. \tag{3}$$

Additionally, this threshold means that, in equilibrium, individuals who choose entrepreneurship but are unproductive as entrepreneurs are likely to have low cost; otherwise, they would have chosen to work.

II.2 Comparative statics: Entrepreneurial spillovers to productivity and cost

Given this framework, consider how entrepreneurship decisions and individuals' z and/or c change because of entrepreneurial spillovers. The spillovers have implications for both the decision to become an entrepreneur (the extensive margin) and the productivity of the marginal entrepreneur (the intensive margin), which motivates my empirical analysis in the remainder of the paper. Here, I consider the partial equilibrium implications of entrepreneurial spillovers (i.e., ignoring any effects of the spillovers on wages), which matches the structure of my individual-level analyses in Sections III and IV, in which the economy is implicitly held fixed. I additionally briefly consider the general equilibrium, in which wages may change with spillovers; this matches the structure of my model in Section V that I use to analyze the aggregate effects of the spillovers.

Suppose there are spillovers that shift the distributions of z and c, e.g., increasing the average z and/or decreasing the average c for individuals who work with entrepreneurial coworkers. How do these spillovers affect individuals' entrepreneurial decisions, as well as the characteristics of entrepreneurs in the economy? In partial equilibrium, the implications of spillovers are straight-forward: increases in z and decreases in c both push individuals towards entrepreneurship, but only increases in z increase the productivity of the

[12] In Lucas (1978), this productivity is known as managerial technology and encompasses both managerial skill and span of control.

[13] The fixed cost c may also capture the mental burden of entrepreneurial risk, etc. See examples of lists of all the decisions entrepreneurs must make from the U.S. Small Business Association (https://www.sba.gov/business-guide/10-steps-start-your-business) and *Forbes* (https://www.forbes.com/sites/allbusiness/2018/07/15/35-step-guide-entrepreneurs-starting-a-business/?sh=34ea1f54184b). Some of these decisions are highly logistical and build up institutional knowledge, while other decisions are more closely linked to the productivity, and thus profitability, of the business.

[14] Note that because c only enters additively in the payoff, optimal N does not depend on c.

[15] This is because production (and thus profits, excluding the fixed cost) increases in z, while the total payoff to entrepreneurship decreases in c. Taking partial derivatives of equation (2), we see that $\frac{\partial z^*(c)}{\partial c} = \left(\frac{\partial \pi(z^*(c);w)}{\partial z^*(c)}\right)^{-1} > 0$.

marginal entrepreneur.

Formally, suppose that individuals learn from their entrepreneurial coworkers. First, if an individual works with more former entrepreneurs who have lower values of c, then they "learn" to lower their own c (e.g., because they learn institutional knowledge from the low-c entrepreneurs). Second, if an individual works with more former entrepreneurs who have higher values of z, then they "learn" to increase their own z (e.g., because they learn entrepreneurial skills that increase their productivity from the high-z entrepreneurs).[16]

As discussed above, both increasing their z and decreasing their c will push individuals towards choosing entrepreneurship, since both increase their relative payoff from entrepreneurship, as seen in equation (2).[17] Holding the wage fixed, an increase in z or decrease in c yields a larger payoff from entrepreneurship, such that an individual is more likely to opt into entrepreneurship.[18]

Meanwhile, spillovers to z and c have different effects on the productivity of the marginal entrepreneur. If an individual's c decreases, they are more likely to choose entrepreneurship regardless of whether they have a lower z, such that spillovers that decrease c lead to marginally less-productive entrepreneurs; formally, because the threshold level of z above which individuals choose entrepreneurship increases with c, as shown in equation (3), reducing c predicts that the marginal entrepreneur has a lower z in partial equilibrium. Spillovers that increase z, however, will increase the entrepreneurial productivity of the marginal entrepreneur, as well as the average productivity (under frequently used distributional assumptions).[19] Taken together, this means that the ultimate partial equilibrium effect of spillovers on the entrepreneurial productivity will depend on which of the two spillovers — i.e., productivity and cost — dominate for the average individual, which is ultimately an empirical question.

Therefore, this conceptual framework demonstrates that I can measure the presence of spillovers by studying the *extensive margin* (i.e., the decision to become an entrepreneur), by leveraging variation in exposure to any (i.e., low c and/or high z) entrepreneurial coworkers; and then disentangle the spillovers in z and c by studying the *intensive margin* (i.e., the quality of entrepreneurs), by leveraging variation in exposure to more productive (i.e., high z) entrepreneurial coworkers. Namely, we want to determine in which box below each individual who works with entrepreneurial coworkers is located:

		Spillovers to c? (i.e., $c\downarrow$)	
		Yes	No
Spillovers to z? (i.e., $z\uparrow$)	Yes	+ extensive margin, +/− intensive margin	+ extensive margin, + intensive margin
	No	+ extensive margin, − intensive margin	no effects

[16] It is also possible that exposure to entrepreneurial coworkers may decrease an individual's z, e.g., if these coworkers give bad advice. Exposure may also increase an individual's c, e.g., if these entrepreneurial coworkers convey how difficult entrepreneurship can be, which could increase the cost to entrepreneurship. Below, I argue that the empirical evidence does not support these alternatives playing dominant roles and exclude these patterns in the model presented in Section V.

[17] Formally, $\frac{\partial \Pr(x=1)}{\partial c} < 0$ and $\frac{\partial \Pr(x=1)}{\partial z} > 0$, where $\Pr(x=1)$ denotes the probability an individual chooses to be an entrepreneur, i.e., the probability that $w \leq \max_N(f(z,N) - wN - c)$.

[18] See Guiso, Pistaferri, and Schivardi (2020) and Guiso and Schivardi (2011) for a complete discussion of how entrepreneurial spillovers within locations push more individuals towards entrepreneurship.

[19] It is possible for spillovers that increase z to decrease the average productivity of equilibrium entrepreneurs through a composition effect, if some low productivity individuals have their productivity increased "just enough" to induce them to choose entrepreneurship without making them high productivity entrepreneurs. As Guiso, Pistaferri, and Schivardi (2020) argue, positive spillovers in productivity increase the average entrepreneurial productivity in general if entrepreneurial productivity is drawn from a log-concave distribution (Barlow and Proschan (1975)), e.g., is distributed as uniform, normal, or exponential; an example of a non-log-concave distribution is a bimodal one.

In Section III, I demonstrate the presence of spillovers by studying the extensive margin. I show that individuals who work with more entrepreneurial coworkers are more likely to subsequently become entrepreneurs themselves. I interpret this positive extensive margin results as indicating the presence of spillovers, i.e., ruling out the southeast box in the table above. Namely, individuals who work with entrepreneurial coworkers learn *something*, although this exercise cannot distinguish between whether they learn to lower their c's or increase their z's.

In Section IV, I disentangle the spillovers to z and c by studying the intensive margin, in order to determine in which of the other boxes exposed individuals are located. I show that individuals who work with more entrepreneurial coworkers (who are high-z and/or low-c) tend to become less productive entrepreneurs, starting smaller firms that are less likely to survive than other new firms; this suggests spillovers to c. However, *if* the entrepreneurial coworkers themselves started relatively productive firms, and thus were likely high-z entrepreneurs, the individuals start relatively productive firms too, suggesting spillovers to z.[20] Through these analyses, I conclude that spillovers to both c and z exist, such that exposed individuals are located in the northwest box. These individuals are more likely to become entrepreneurs, but their predicted success depends on their relative exposure to high-z versus low-c entrepreneurial coworkers.

In Section V, I study the aggregate implications of these entrepreneurial spillovers by modeling entrepreneurial spillovers in the presence of general equilibrium wage effects. Compared to the partial equilibrium, which is informative for the reduced form analyses in which I consider individual-level variation in exposure to entrepreneurial coworkers holding fixed the economy, the ultimate impact of spillovers on entrepreneurship depends on how the equilibrium wage responds. For example, large spillovers that increase some individuals' z's can actually decrease total entrepreneurship. In the extreme case, if one individual's z is increased substantially, they may demand enough labor, putting upward pressure up the wage, such that all other individuals choose to work for them. See Section V for the full treatment of the general equilibrium.

III Extensive margin spillovers: Entry to entrepreneurship

I estimate entrepreneurial spillovers across coworkers by leveraging variation in individuals' exposure to coworkers with prior entrepreneurial experience, conditional on rich controls. I find evidence of positive *extensive margin* spillovers: individuals who work with one standard deviation (10 percentage points) higher share of entrepreneurial coworkers are 2.5 percentage points more likely to become entrepreneurs themselves within the next five years, an 8% increase relative to the average likelihood. I show that these patterns are supported by survey evidence and are plausibly causal, not being wholly driven by entrepreneurial-type individuals selecting into particular firms or establishments nor by common geographical or industrial business environment shocks. Section A.II presents additional evidence against several alternative mechanisms.

III.1 Empirical strategy: Leverage variation in exposure to entrepreneurial coworkers

In order to study the extensive margin, I estimate an ordinary least squares specification with rich controls that leverages cross-individual variation in exposure to entrepreneurial coworkers.

[20]The positive intensive margin results for individuals exposed to more productive entrepreneurial coworkers could also arise if these successful coworkers dissuade entrepreneurial ventures that are likely to fail, i.e., generating positive selection into entrepreneurship. I provide evidence against this option in Section III, where I show that, in general, exposure to more productive entrepreneurial coworkers also predicts entrepreneurship. That is, productive entrepreneurial coworkers do not appear to dissuade entrepreneurship, on average. Additionally, as noted in footnote 19, it is possible for spillovers that increase z to lead to lower average productivity through a composition effect. The fact that I measure the positive intensive margin results for individuals exposed to more successful entrepreneurs suggests that the marginal impact of spillovers that increase z is positive.

I find that if an individual interacts more with former entrepreneurs, then they are more likely to become an entrepreneur subsequently. I compare the future entrepreneurship of individuals who work with more coworkers who were recently entrepreneurs to those who work with proportionally fewer entrepreneurial coworkers. Effectively, I want to compare individuals who are very similar, both in terms of their own demographics and entrepreneurship experience and their current firms, but who have different exposure to entrepreneurial experience.

I estimate the following linear probability model:[21]

$$\begin{aligned}\text{Future entrepreneurship}_{i,n,s} = \alpha + \beta\text{Share of coworkers with entrepreneurship}_{i} \\ + \mathbf{X}_{i,n,s}\delta + \xi_{i,n,s},\end{aligned} \tag{4}$$

where Future entrepreneurship$_{i,n,s}$ is an indicator equal to 1 if individual i, whose 2004 primary establishment belongs to industry n (given by a 6-digit NAICS code) and is located in state s, becomes an entrepreneur within the next 5 years (i.e., from 2005 through 2009), and 0 otherwise.[22] The key coefficient of interest is β on the share of individual i's 2004 primary establishment coworkers who were entrepreneurs within the past 5 years; the share is a proportion and lies between 0 and 1.[23] This coefficient measures the relationship between having more coworkers in 2004 with recent entrepreneurship experience and the likelihood of becoming an entrepreneur in the near future.[24]

The model also contains a vector of controls $\mathbf{X}_{i,n,s}$ that are chosen to bolster a causal interpretation of β measuring the causal effect of exposure to entrepreneurial coworkers on an individual's future entrepreneurship. Intuitively, by including controls, I make a "selection on observables" argument: conditional on these controls, exposure to entrepreneurial coworkers is exogenous. To this end, I include controls that may correlate with both the outcome and exposure variables, such that excluding these controls would generate endogeneity (i.e., omitted variable bias).

I control for several variables that, as shown in Table 1, are correlated with an individual's future entrepreneurship. Namely, I control for individual i's primary establishment's log employment[25] because future entrepreneurs tend to work at smaller establishments. Similarly, I control for individual i's own previous entrepreneurship between 1999 and 2003 and their current entrepreneurship in 2004, since entrepreneurship is highly serially correlated. I control for individual i's 2004 log annual earnings at their primary firm, since future entrepreneurs tend to have higher earnings, perhaps because higher paid individuals are more pro-

[21]In unreported results, I confirm that my extensive margin results are similar if estimated as logistic model, rather than a linear probability model.

[22]This indicator for being a future entrepreneur is zero if the individual either appears in my sample of states in 2005-2009 as a worker only (i.e., as a worker, but not as an entrepreneur) or does not appear in my sample of states (e.g., because they are unemployed, not in the labor force, or working in a state outside of my sample.)

[23]Specifically, this variable is calculated by counting the number of individual i's coworkers who were entrepreneurs (started a firm) between 1999 and 2003, and then dividing this count by the total number of coworkers. I exclude coworkers who are currently entrepreneurs in 2004.

[24]While I model entrepreneurial spillovers here as linear-in-means (since the share of coworkers who were recently entrepreneurs is a mean), the spillovers could take other forms. For example, it is possible that an individual only needs exposure to a single entrepreneur in order to experience spillovers. I estimate an alternative version of model 4 in which I consider exposure to *any* entrepreneurial coworkers. Inspired by Nanda and Sørensen (2010), I break this out by establishment size, under the assumption that an individual is more likely to run into a single particular employee at a smaller establishment. As Table A.4 shows, the estimates of this model suggest that indeed, individuals who work with any entrepreneurial coworkers are more likely to subsequently become entrepreneurs, and this relationship is strongest at smaller establishments: individuals at establishments with fewer than 25 employees are 17.7% more likely to become entrepreneurs if they work with at least one entrepreneurial coworker, relative to the mean, while those at establishments with more than 100 employees are 10.9% more likely to become entrepreneurs if they have any entrepreneurial coworkers.

[25]For this measure of employment, I only count individuals for whom the establishment is their primary establishment. This is the group of workers who are considered when identifying coworkers.

ductive or have more access to start-up capital. Furthermore, I control for a vector of demographic controls, including age fixed effects and indicators for sex, race, four-bin education, and birth in the United States,[26] because, compared to the general workforce, future entrepreneurs tend to be younger, male, higher-educated, White or Asian, or born outside the U.S. Many of these variables may correlate with individual i's exposure to entrepreneurial coworkers, making it important to control for them; for example, workers of particular demographics (and consequently similar entrepreneurial proclivities) may cluster at certain firms.

Additionally, I control for detailed industry and state fixed effects based on the industry and location of their 2004 primary establishment. Controlling for industry fixed effects is important because entrepreneurship rates vary dramatically by industry; for example, around 2004, many new firms entered the construction sector, perhaps due to booming housing demand (Figure 2). Controlling for state fixed effects is similarly important because there may be location-based policies that promote both future entrepreneurship and past entrepreneurship of coworkers.

The model also includes an idiosyncratic draw, $\xi_{i,n,s}$. Note that the share of individual i's coworkers who were previously entrepreneurs is correlated with that share for their coworkers themselves; treatment is effectively defined at the establishment level. For this reason, I estimate this model with standard errors clustered at the establishment level.

Before I present the estimates of this model, recall from Section II that both the sign and magnitude of β are not known ex-ante, such that both the sign and magnitude are empirical questions. That is, β measures the linear prediction of having more entrepreneurial coworkers on future entrepreneurship, holding fixed the set of controls. If we interpret model (4) as estimating a causal entrepreneurial spillover, β could be positive if individuals are inspired or taught by entrepreneurial coworkers. Alternatively, β could be negative if these entrepreneurial coworkers discourage entrepreneurship. These spillovers could be large or small in magnitude.

III.2 Main results: Positive extensive margin spillovers

Table 3 presents the point estimates from model (4) as controls are gradually added. As the table shows, individuals who work with proportionally entrepreneurial coworkers are more likely to become entrepreneurs in the future, regardless of the inclusion of controls. As more controls are added, this relationship decreases marginally but remains relatively stable.

In the full specification (column 8), the coefficient on the share of coworkers with entrepreneurial experience is 0.025: this predicts that an individual whose entire set of coworkers have entrepreneurial experience is 2.5 percentage points more likely to become an entrepreneur themself, compared to an individual who works with no entrepreneurial coworkers.[27] Recall that only 3.1% of the sample become entrepreneurs subsequently, such that 2.5 percentage points is very large relative to 3.1%, suggesting an 80% increase relative to the mean.

However, this interpretation may be misleading, since very few individuals work with all former entrepreneurs. Instead, consider an increase in one standard deviation: the estimated model predicts that individuals who work a one standard deviation (9.5 percentage points) higher share of entrepreneurial coworkers are 0.236 percentage points more likely to become entrepreneurs in the next five years. This gap is still large: a 0.236 percentage point increase in the predicted future entrepreneurship maps into a 7.6% increase,

[26] As noted above, non-imputed demographics are not available for all individuals. In regressions below, I assign the mean demographic values to those with missing demographics and then include as controls indicators for missing the various demographic values.

[27] Figure A.1 demonstrates that the relationship is linear for the majority of the distribution of exposure and generally concave.

relative to the mean;[28] this increase is comparable to the prior findings in the literature.[29]

To provide a simple evaluation of the size of this estimate, I conduct a back-of-the-envelope calculation to approximate how much the spillovers boost aggregate entrepreneurship. I predict the number of "additional" future entrepreneurs that start firms in the presence of spillovers by multiplying the coefficient on the share with the mean share of coworkers with entrepreneurship experience (0.03356) and the number of individuals (46.68 million). This calculation yields a predicted additional 39,000 future entrepreneurs, which amounts to a 2.75% increase.[30]

While this back-of-the-envelope calculation is inherently simple, ignoring any general equilibrium forces or dynamics of how spillovers aggregate over time, it does suggest a meaningful role for spillovers: spillovers boost aggregate entrepreneurship by 3%. In Section V, I return to this aggregation exercise, taking into account general equilibrium effects and dynamics.

III.3 Direct survey evidence of spillovers

In this section, I provide direct evidence of entrepreneurial spillovers that support the positive spillovers estimated above: entrepreneurs who previously worked with more entrepreneurial coworkers are more likely to report that entrepreneurial role models led them to start firms. After matching entrepreneurs in the LEHD to owners in the ASE survey data, I find that individuals who worked with more entrepreneurial coworkers, especially ones who were relatively successful, and subsequently become entrepreneurs are more likely to say that entrepreneurial coworkers influenced their decision to start a firm.

For the top four owners of each firm in the 2014-2016 surveys, the ASE asks "How important to Owner [n] are each of the following reasons for owning this business?" Respondents are faced with a list of options,[31] each of which they can label "Not Important," "Somewhat Important," or "Very Important." While there is no direct question about previous coworkers, the option "an entrepreneurial friend or family member was a role model" may be interpreted to contain coworker role models.[32]

Given this survey question, I estimate whether individuals with higher shares of coworkers with previous entrepreneurship are more likely to cite this "role model" reason for their entry to entrepreneurship, conditional on appearing the ASE after working with those coworkers. I estimate model (4) but replace future entrepreneurship as the outcome with stating that role models were at least somewhat important.

There are two challenges to running this analysis. First, the ASE begins in 2014; since exposure to entrepreneurship may affect the quality of a future entrepreneur's firm (see Section IV), matching individuals in 2004 to firms in the ASE may produce a very selected group of individuals whose entrepreneurial firms were successful enough to survive to 2014. Furthermore, entrepreneurs in 2014 may have imperfect recall

[28] This is calculated by the following: one standard deviation of share of coworkers with entrepreneurial experience (0.095) times the coefficient on the share of coworkers with entrepreneurial coworkers (0.025) divided by the share of individuals who become entrepreneurs (0.03120).

[29] In Denmark, Nanda and Sørensen (2010) find that a one standard deviation in an individual's coworkers' entrepreneurship predicts a 4% increase in their future entrepreneurship, relative to the mean. In Italy, Guiso, Pistaferri, and Schivardi (2020) find that a one standard deviation in an individual's local firm density at age 18 predicts a 8% increase in their entrepreneurship, relative to the mean. In Sweden, Giannetti and Simonov (2009) find that a one standard deviation increase in an individual's local entrepreneurship predicts a 5.7% increase in their entrepreneurship, relative to the mean.

[30] I reach a 2.75% increase by dividing the predicted number of entrepreneurs (number of observations $*$ mean share $*$ coefficient, i.e., 46,680,000 $*$ 0.03356 $*$ 0.02494 = 39,000) by difference between the actual number (number of observations $*$ future entrepreneurship rate, i.e., 46,680,000 $*$ 0.03120 = 1,456,416) and the predicted number.

[31] These include: "wanted to be my own boss," "flexible hours," "balance work and family," "opportunity for greater income/wanted to build wealth," "best avenue for my ideas/goods/services," "couldn't find a job/unable to find employment," "working for someone else didn't appeal to me," "always wanted to start my own business," "an entrepreneurial friend or family member was a role model," and "other."

[32] In a survey of Dutch entrepreneurs, Bosma et al. (2012) find that entrepreneurs' self-reported role models tend to be their family members, friends, former colleagues, or former employers and are very rarely business icons.

of their motivations and experiences a decade earlier. For these reasons, I estimate this model on a new sample: individuals in 2009-2012 who become an entrepreneur in 2013[33] and whose entrepreneurial firm is surveyed in at least one of the three ASE rounds; I restrict to the last year I see each individual within the 2009-2012 and measure coworkers in that year.

The second challenge lies in that the ASE does not contain identification numbers for the owners, so I cannot directly match the individuals I identify as entrepreneurs in the LEHD to the ASE owners.[34] Instead, for individuals in the LEHD who become entrepreneurs and whose entrepreneurial firm is surveyed in the ASE, I check whether their demographics align with those of any of the owners described in the ASE. Specifically, I match the entrepreneurs in the LEHD to ASE owners of their entrepreneurial firm on the basis of sex, education, race, age, and birth country and keep the sample of entrepreneurs who match to at least one owner; for individuals who match to more than one owner along these demographics, I average across the owners' responses.[35] In the resulting sample of 7,000 entrepreneurs, 55% of individuals say that entrepreneurial role models were at least somewhat important to their decision to become an entrepreneur.

Consistent with the presence of spillovers, estimates of model (4) show that entrepreneurs who previously worked with more entrepreneurial coworkers are more likely to report that entrepreneurial role models were important to their decision to start a firm. Specifically, entrepreneurs who worked with a one standard deviation (15.5 percentage point) higher share of coworkers with entrepreneurial experience are 2.4% more likely to report that entrepreneurial role models were at least somewhat important for their entrepreneurship, relative to the mean.[36] In other words, the individuals who I predict to have been influenced by entrepreneurial models, via their exposure to entrepreneurial coworkers, are indeed more likely to report this influence, consistent with these spillovers actually taking place.

III.4 Robustness: Addressing potential identification concerns

While I argue above that model (4) controls for important possible sources of endogeneity, there remains the possibility that other non-observed characteristics generate endogeneity problems. As summarized in Sacerdote (2014) it is difficult to estimate causal peer effects, such as entrepreneurial spillovers across coworkers, from observational data for three categories of reasons: selection into peer groups, common shocks, and the reflection problem. I discuss each of these in turn and provide evidence against these concerns.

III.4.1 Selection into peer groups

In this paper, selection into peer groups is perhaps the greatest concern: individuals do not randomly sort into firms or establishments, such that exposure to entrepreneurial coworkers may reflect some confounding force beyond those accounted for in the controls rather than causal peer effects. This could happen for two broad reasons. First, entrepreneurship-prone individuals may cluster at certain firms or establishments with hopes of learning entrepreneurial skills or using these firms or establishments as launching pads for

[33] Ideally, I would study firms in the ASE that start in 2014, 2015, or 2016; unfortunately, the currently available LEHD ends (with amply available SEIN to FIRMID matching) in 2013.

[34] See footnote 93 for a discussion of the limited person identifiers in the ASE.

[35] In each year of the ASE, information is reported for up to 4 owners; some firms are re-sampled across the survey waves, such that each firm will have at least 1 owner and up 12. I restrict to owners who self-identify as founders of the firm. I match individuals on non-imputed sex, education, race, age bin, and birth in the U.S.; for each individual, I allow for up to 1 of these categories to not match in order to call the match a success. I restrict to individuals who match to at least one owner; 80.4% of individuals who are matched are uniquely matched to only one owner in at least one year.

[36] This calculation is a follows: one standard deviation in the share of coworkers with entrepreneurship (0.155) times the coefficient on the share of coworkers with entrepreneurship (0.084) divided by the share of entrepreneurs who report that entrepreneurial role models were at least somewhat important (0.5507).

entrepreneurial careers, such that spillovers reflect employer effects rather than coworker effects. Second, entrepreneurship-prone individuals may cluster at certain firms or establishments for a reason unrelated to entrepreneurship. For example, if entrepreneurial-type individuals tend to have higher human capital, they may cluster at certain workplaces because of their similar human capital. To address these concerns beyond controlling for individuals' own recent entrepreneurship experience, I perform several robustness exercises, starting with considering selection at the largest scope — into firms — and then narrow toward selection at smaller scopes — into establishments or worker groups.

Selection into firms If entrepreneurship-prone individuals cluster at certain firms, regardless of reason, then there should be nothing inherently "special" about an individual's establishment coworkers within their firm. That is, the relationship from model (4) should be similar if instead of considering establishment coworkers, I estimate the relationship between an individual's future entrepreneurship and the entrepreneurial experience of employees at their firm, particularly employees at other establishments within the same firm with whom they may never interact (and thus from whom they should not learn). I estimate the following two similar models:

$$\begin{aligned}\text{Future entrepreneurship}_{i,n,s} = \alpha &+ \beta_1 \text{Share of establishment coworkers with entrepreneurship}_i \\ &+ \beta_2 \text{Share of firm workers with entrepreneurship}_i \\ &+ \mathbf{X}_{i,n,s}\delta + \phi \log(\text{Employment at firm})_i + \xi_{i,n,s},\end{aligned} \tag{5}$$

which is identical to model (4), except for the inclusion of a term measuring the share of all coworkers at individual i's firm who were entrepreneurs between 1999 and 2004, and the log total employment at the firm; and

$$\begin{aligned}\text{Future entrepreneurship}_{i,n,s} = \alpha &+ \beta_1 \text{Share of establishment coworkers with entrepreneurship}_i \\ &+ \beta_2 \text{Share of other-establishment workers with entrepreneurship}_i \\ &+ \mathbf{X}_{i,n,s}\delta + \phi \log(\text{Employment at other establishments})_i + \xi_{i,n,s},\end{aligned} \tag{6}$$

which is identical to model (4), except for the inclusion of a term measuring the share of the workers at individual i's firm, at the firm's establishments other than i's, who were entrepreneurs between 1999 and 2004, and the log total employment at other establishments.

For model (6), I consider three different categories of other establishments. First, I consider all other establishments at the firm (in my sample). Second, I consider establishments located in the same state but belonging to a different industry (2-digit NAICS code); this group is useful if we are concerned that my results reflect clustering at establishments within a firm *within certain states*. Third, I consider establishments located in the same industry (2-digit NAICS code) but a different state; this set is useful if we are concerned about selection into particular establishments within a firm *within the same industry*.[37] It is worth noting that model (4) can only be estimated for firms that have multiple establishments (of the given category) in my sample, and so I also estimate of model (4) for these samples for comparison.

If the previously estimated positive spillovers are driven by selection into firms, rather than coworker spillovers, then we should see the following patterns. In model (5), firm effects may load onto β_2, the

[37] In the LEHD data, establishments located in the same state but a different industry (or same industry but a different state) are identified by having a different SEIN (but the same FIRMID).

coefficient on the share of workers at the firm with entrepreneurial coworkers, such that β_1 should be zero (or the shares could be collinear). In model (6), firm effects should mean that there is no difference between exposure to entrepreneurial establishment coworkers and "exposure" to entrepreneurial workers at other establishments within the same firm, such that β_1 and β_2 should take on the same value.

Table 4 presents the findings of this analysis. Spillovers are concentrated within-establishment: regardless of which set of other establishments at the firm I consider, an individual's future entrepreneurship is disproportionately related to their establishment coworkers' past entrepreneurship, rather than to the entrepreneurial experience of other employees at the firm. This is true for estimates of both models (5) and (6). In the case of model (5), I find that all evidence of spillovers load onto establishment coworkers, rather than firm workers in general (column 3). In the case of model (6), I find substantially larger coefficients on exposure to entrepreneurial establishment coworkers compared to entrepreneurial other-establishment workers. In particular, when I horse-race the entrepreneurial share of an individual's establishment coworkers with that of workers at all other establishments in the firm (column 5), the coefficient on the establishment coworkers is more than 9 times larger than the coefficient on the other-establishment workers. Similar gaps appear for the alternative categories of other establishments, i.e., in the same state or industry. While there is some scope for general firm patterns (i.e., the coefficients on share of other-establishment coworkers who were entrepreneurs are nonzero), the spillover pattern is dominated by establishment patterns.

Selection into establishments While the above exercise demonstrates that the spillovers are not driven by selection into particular firms, or into particular states or industries within particular firms, it could be the case that entrepreneurship-prone individuals actually cluster into specific establishments within firms, such as headquarters.

I argue that the spillovers do not wholly reflect establishment effects. I do this by considering spillovers across individuals who are employed at the same establishment in different years, i.e., individuals who are "placebo coworkers" to each other and whose tenures do not overlap. This strategy leverages the assumption that individuals should only learn from individuals with whom they have interacted and is reminiscent of empirical designs in the social networks literature, such as Caldwell and Harmon (2019).

Specifically, I estimate a version of model (4) for two different subsamples. First, for individuals who join their firms in 2004, I evaluate the entrepreneurial effects of their true coworkers in 2004 versus workers who left the establishment in 2003 or earlier. Second, for individuals who leave their firms in 2004, I evaluate the effects of their true coworkers in 2004 versus workers who join the establishment in 2005 or later. In both cases, the individuals should not interact with, and thus potentially learn from, their non-overlapping placebo coworkers.

For these subsamples, I estimate several versions of model

$$\begin{aligned}\text{Future entrepreneurship}_{i,n,s} = \alpha &+ \beta_1 \text{Share of coworkers with entrepreneurship}_i \\ &+ \beta_2 \text{Share of year-P placebo coworkers with entrepreneurship}_i \\ &+ \mathbf{X}_{i,n,s}\delta + \phi \log(\text{Employment of year-P placebo coworkers})_i + \xi_{i,n,s},\end{aligned} \tag{7}$$

which is identical to model (4), except for the inclusion of a term measuring the share of the workers at individual i's establishment, who were last/first at the firm in year P, who were entrepreneurs between year $P-5$ and year P, and the log total employment of these placebo coworkers.[38]

[38]This means that I am comparing workers' entrepreneurial experience relative to when they first or were last at the firm,

I estimate this only for individuals who either join their firm in 2004 (when P is a year prior to 2004) or are last employed ("leave") in 2004 (when P is a year after 2004), and I estimate this for placebo coworkers who are last at the firm in 1999, ..., 2003 and those who are first at the firm in 2005, ..., 2009.[39]

Table 5 shows estimates of these regressions, suggesting that individuals in both samples experience spillovers disproportionately from their true 2004 coworkers. The coefficients on the share of placebo coworkers who were recently entrepreneurs are smaller than those on the share of true overlapping coworkers who were recently entrepreneurs.

For example, when I horse-race spillovers from true coworkers to individuals who left the firm in the year before the individual joined (Panel A, column 11 of Table 5), the coefficient on the share of true coworkers who were recently entrepreneurs is over 3.5 times larger than the coefficient on these placebo coworkers.[40] The gap is smaller when I consider individuals who leave the firm in 2004 but still apparent: for these individuals, the coefficient on the share of true coworkers who were recently entrepreneurs is over 1.5 times larger than the coefficient on the share of placebo coworkers who join in the next year who were recently entrepreneurs (Panel B, column 3).

The fact that the coefficients on the placebo coworkers are nonzero suggest that there is some persistence of entrepreneurial spillovers at the establishment level, but the relative size of the coefficients on the true coworkers demonstrates the relevance of concurrent establishment coworkers. That is, there is something *special* about concurrent coworkers in terms of entrepreneurial spillovers, above and beyond any workers at the establishment in past or future years, such that the spillovers are not driven entirely by establishment effects.

Selection into coworker groups Beyond selection into particular firms or establishments, entrepreneurship-prone individuals could also select based on the coworkers themselves. To address this concern, I consider two analyses.

First, I consider spillovers from coworkers who join the firm before and after an individual joins (but who are still employed at the establishment in 2004); if an individual joins an establishment to work with particular coworkers, then they may only appear to learn from the coworkers who were already employed at the firm before they joined, whom they could select on when joining. Instead, when I estimate model (4), splitting the coworkers into bins of when they join the firm, I find that individuals also learn from coworkers who join after them. As shown in Table A.5, the largest coefficient is actually on the share of coworkers who were entrepreneurs and joined after the individual.[41] I take the fact that all coefficients on the entrepreneurial coworkers are positive, regardless of when the coworkers joined the firm relative to the individual, as evidence that the extensive margin spillovers are not wholly driven by coworkers who joined

instead of always comparing 1999-2003 entrepreneurship.

[39] An individual "joins" a firm in the first year that they earn at the firm (not necessarily the first year the firm is their primary employer) and "leaves" the firm in the last year that they earn at the firm, within 1994-2013. I make the further restriction to only consider individuals at establishments with sufficient flows of workers, i.e., establishments with individuals who leave (placebo coworkers) in 1999, 2000, 2001, 2002, *and* 2003 for analysis of individuals who join their firms in 2004 (such that the samples are consistent across different P's); and similarly establishments with individuals who join (placebo coworkers) in 2005, 2006, 2007, 2008, *and* 2009 for analysis of individuals who leave (last earn at) their firms in 2004. Table 5 presents the estimates of these regressions.

[40] Additionally, the results are not very different when considering the variables separately, without horse-racing (e.g., column 10 vs. 11); this suggests that entrepreneurship is not actually extremely correlated within establishments over time, providing additional evidence against selection concerns.

[41] Note that for all coworkers, whether they joined before, in the same year, or after the individual, I measure recent entrepreneurship between 1999 and 2003. This means that coworkers who joined before the individual (and thus joined in an earlier calendar year) and who were entrepreneurs between 1999 and 2003 might be differently selected than those who join after the individual. For instance, these coworkers may have been less successful as entrepreneurs, and hence returned to standard work more quickly. For this reason, the relative magnitudes in Table A.5 should be interpreted with caution

the firm after the individual, i.e., who the individual may have known would be their coworker when they joined the firm.

Second, as Jarosch, Oberfield, and Rossi-Hansberg (2021) argue for the case of human capital spillovers, if individuals truly seek out entrepreneurial coworkers, then this should (in a competitive, full information equilibrium sense) be reflected in their wages. That is, if exposure to entrepreneurial coworkers is a compensating differential, we might see individuals accept lower wages in exchange for this exposure. Empirically, this is not the case. As Table A.6 shows, when I estimate model (4) and replace future entrepreneurship with current earnings as the outcome (and control for past earnings instead of current earnings) for new hires, I see that individuals who join establishments with more entrepreneurial coworkers earn, if anything, higher earnings. Conditional on past earnings, a new hire with a one standard deviation (8.9 percentage point) higher share of coworkers with recent entrepreneurship is predicted to have 1.4% higher earnings. While it is still possible that some individuals seek out, and are willing to accept lower wages for, the opportunity to work with more former entrepreneurs, this story does not appear to be relevant, on net.

III.4.2 Common shocks

Common shocks could drive both an individual's future entrepreneurship and their coworkers' past entrepreneurship. That is, it is possible that there is some force outside of the firm or establishment effects discussed above, for instance industry business cycles or local pro-business government policies, that could generate fluctuations in the attractiveness of entrepreneurship. These fluctuations could drive both an individual's future entrepreneurship and their coworkers' past entrepreneurship.

However, there is little space nor evidence for these common shocks, conditional on the rich set of controls in model (4). Model (4) includes detailed 6-digit industry and state fixed effects, such that any common shocks would have to operate within these categories. As robustness, in Table A.7, I additionally estimate model (4) including state-by-6 digit industry fixed effects and find consistent results. For single-location establishments, I can also identify the establishments' ZIP codes from the LBD; as presented in Table A.8, for the sample of individuals at these establishments, I find the estimated spillovers are actually larger when I include ZIP code and ZIP code-by-6-digit industry fixed effects. Common shocks would have to operate within these ZIP code-industry pairs in order to drive the estimated spillovers.[42]

Further, it is not the case that the results are driven by the five-year time windows, which could map to business cycles. Instead, if I estimate model (4) for exposure to coworkers who were entrepreneurs in each of the past 10 years, the results are similar regardless of when the coworkers were entrepreneurs, as shown in Figure A.2. Similarly, if I estimate separate versions of model (4), considering exposure to entrepreneurial coworkers whose entrepreneurship happened more or less recently; as shown in Table A.9, the positive spillovers already exist when I only consider exposure to coworkers who were entrepreneurs in the past year (i.e., in 2003) and persist if I consider exposure to coworkers who were entrepreneurs in the past years, up to 10 years (i.e., between 1994 and 2003).

III.4.3 The reflection problem

The canonical reflection problem, first described in Manski (1993), captures bias created when trying to estimate the relationship between an individual and their peers' outcomes when these outcomes are measured

[42]For individuals at single-location establishments, in the baseline specification (with state and industry fixed effects), a one standard deviation (13.2 percentage point) increase in the share of coworkers with recent entrepreneurship experience predicts a 0.17 percentage point increase in the likelihood of future entrepreneurship, 3.9% of the mean outcome. When I include ZIP code-by-industry fixed effects, a one standard deviation increase predicts a 0.26 percentage point increase, 5.8% of the outcome.

at the same time. The reflection problem is not relevant for this paper because I measure coworkers' entrepreneurship in the past, and individuals' entrepreneurship in the future, and it is unlikely that an individual's future entrepreneurship affects their coworkers' past entrepreneurship, controlling for their past entrepreneurship.[43]

III.5 Heterogeneity by characteristics of coworkers' past entrepreneurial firms

Because entrepreneurial experience can vary vastly in success, and thus likely enjoyability, it is possible that these extensive margin spillovers may vary by the characteristics of the coworkers' past entrepreneurial firms. Indeed, I find that the positive spillovers are generally amplified when the entrepreneurial coworkers ran relatively successful firms.

Why might the spillovers vary by the quality of the entrepreneurial coworkers' firms? Entrepreneurial experience can vary significantly, leading to coworkers potentially having different skills and evaluations of entrepreneurship. For instance, coworkers whose entrepreneurial firms failed may express the woes and stresses of entrepreneurship, dissuading other individuals from becoming entrepreneurs. Meanwhile, coworkers whose entrepreneurial firms were relatively successful may present more optimistic views of entrepreneurship, or may be able to pass on knowledge and skills that make prospective entrepreneurs expect success for themselves. Or, these relatively successful entrepreneurs may too dissuade entrepreneurship, if they are able to provide criticism against poorly formed business ideas, as in Lerner and Malmendier (2013).

I explore this heterogeneity by estimating whether the extensive margin spillovers are increased or decreased if an individual's entrepreneurial coworkers ran more successful firms. I estimate an extended version of model (4):

$$\begin{aligned}\text{Future entrepreneurship}_{i,n,s} = \alpha &+ \beta \text{Share of coworkers with entrepreneurship}_i \\ &+ \gamma \text{Share of coworkers with successful entrepreneurship}_i \\ &+ \mathbf{X}_{i,n,s}\delta + \xi_{i,n,s},\end{aligned} \tag{8}$$

where I add as an explanatory variable the share of an individual's coworkers who were both entrepreneurs in the past 5 years and whose firms were successful. I employ several measures of success here: whether the firm survived past the first year(s) and whether the firm was among the top 10% of firms that entered in the same year and industry (6-digit NAICS) in terms of employment, payroll, revenue, and productivity.

Table 6 presents the estimates of model (8): conditional on general exposure to entrepreneurial coworkers, individuals who work with more *successful* entrepreneurs are even more likely to become entrepreneurs themselves. For example, conditional on general exposure to entrepreneurs, an individual with a one standard deviation (2.5 percentage points) higher share of coworkers who were entrepreneurs at firms in the top 10% of entry year log employment is 0.05 percentage points more likely to become an entrepreneur, a 1.7% increase relative to the mean. That is, on net, neither unsuccessful nor successful (by these metrics) entrepreneurial coworkers dissuade entrepreneurship in general.

In Section A.IV, I provide evidence to reconcile the lack of dissuasion in general with the findings of Lerner and Malmendier (2013), by showing that exposure to entrepreneurial coworkers who are arguably similar to the Harvard MBAs studied in Lerner and Malmendier (2013) predicts a lower probability of starting a relatively unsuccessful firm. I further explore what the characteristics of coworkers' entrepreneurial firms

[43] I follow Lerner and Malmendier (2013) in making this argument.

predict for future entrepreneurs' firms in Section IV.

III.6 Heterogeneity by characteristics of individuals and their coworkers

There is also substantial heterogeneity in these extensive margin results by the characteristics of the individuals; these differences emphasize that context can matter substantially for entrepreneurial learning.[44]

Sector of individual's establishment Because workplaces and entrepreneurship patterns vary by industry, it is plausible that spillovers may vary dramatically across sectors.[45] In fact, most sectors have similar coefficients to the aggregate coefficient, with some exceptions. Figure 5 shows the extensive margin spillovers by the sector of the individual's current establishment, estimated in a single regression by interacting the share of coworkers who were recently entrepreneurs with indicators for each sector, while continuing to include industry fixed effects that control for baseline differences in future entrepreneurship rates. There appears to be few spillovers for workers in the agriculture, utilities, and health sectors (which likely have high entry costs due to regulation) but substantial spillovers in the management and accommodation and food services sectors.[46]

The fact that spillovers exist in most sectors but are strongest in the accommodation and food service sector suggests two conclusions. First, these spillovers exist across the economy — these spillovers are commonplace, and are not driven by the culture or structure of a single sector. Second, because the spillovers are largest in the relatively low-technology accommodation and food services sectors, these spillovers are unlikely to be predominantly transmitting knowledge of complex technologies or promoting innovation.

Ages of individuals and their coworkers I investigate heterogeneity in spillovers by age, both in terms of the age of the individuals and the ages of their entrepreneurial coworkers.[47] Both of these dimensions are important, since they are informative about who is affected by spillovers and yield some predictions on the future relevance of spillovers as the population ages.

First, I estimate model (4) but interact the exposure variable with dummies capturing the age of the individuals, continuing to include age fixed effects that account for baseline differences in future entrepreneurship rates. The estimates from this model, as shown in panel A of Figure 3, show an inverse-U relationship between individual age and spillovers: younger individuals are the most likely to become entrepreneurs after working with more entrepreneurial coworkers, with the largest spillovers experienced by individuals around the age of 30. This pattern does not just reflect the similarly inverse-U entrepreneurship pattern across age (Figure 1); rather, this pattern persists when I normalize the coefficients by each age's entrepreneurship rate, as shown in panel B of Figure 3.

The pattern of younger individuals experiencing stronger spillovers is consistent with the notion that younger individuals tend to be the most entrepreneurially opportunistic: Bernstein et al. (2018) argue that young and skilled individuals drive new firm creation in response to local demand shocks. Younger individuals "learning" more in terms of entrepreneurship is also consistent with general learning patterns in

[44]See Section A.III for additional heterogeneity analyses, specifically showing that spillovers are not concentrated amongst high earners.

[45]For instance, Kerr and Kominers (2015) argue that benefits to individual interactions drive clustering of technology firms in Silicon Valley. This suggests that we might see large entrepreneurial spillovers in the information or high tech sector.

[46]These patterns are similar if I normalize the coefficients by the sector-specific entrepreneurship rate (i.e., the mean outcome). The management sector consists of firms that manage companies and enterprises, such as holding companies and private equity firms.

[47]The recent literature has highlighted that entrepreneurship patterns vary dramatically by age: older individuals are disproportionately less likely to become entrepreneurs than younger ones (see Figure 1), but tend to start more successful firms (Azoulay et al. (2018)). These patterns have led to arguments that population aging has driven declines in firm entry and business dynamism (Engbom (2019); Hopenhayn, Neira, and Singhania (2020); Karahan, Pugsley, and Şahin (2019)).

the workforce, as Jarosch, Oberfield, and Rossi-Hansberg (2021) argue that individuals below the age of 40 learn human capital from their coworkers more quickly than older individuals. Part of this pattern might also be driven by younger individuals having the most to learn about entrepreneurship; older individuals likely have already been exposed to entrepreneurs during their time in the labor market, and so might have less to learn from current coworkers.

Second, I investigate how spillovers vary with the ages of the entrepreneurial coworkers. I estimate model (4) but consider exposure to entrepreneurial coworkers of specific ages (controlling for the distribution of coworker ages at the establishment). Figure 4 shows the estimates of this model, demonstrating that spillovers tend to decrease with the age of the entrepreneurial coworkers: individuals are less likely to become entrepreneurs if their entrepreneurial coworkers are older.

While the above two analyses suggest that spillovers are largest when individuals are younger and entrepreneurial coworkers are younger, it is not the case that the spillovers are restricted to individuals of similar ages. Instead, when I interact the age of the individual with the ages of their entrepreneurial coworkers, as shown in Table A.10, I find that individuals tend to learn from coworkers who are older than them.[48] This may be because older coworkers are more likely to serve as role models or mentors.

Taken together, these analyses suggest that population aging may have mixed effects on the role of spillovers. On the one hand, having fewer younger individuals in the economy may reduce the number of potential "students" to entrepreneurship. On the other hand, having more older individuals may yield more entrepreneurial "teachers," depending on the remaining age composition and how workers sort across firms.

Social groups I next investigate whether spillovers vary along several dimensions that likely relate to how much individuals actually interact with their coworkers in the workplace and how personally relevant the experiences of coworkers are to individuals.

First, I consider individuals who are more likely to be in the same work peer group or occupation. While I do not observe actual peer groups or occupations in the data, I proxy for these with earnings. I estimate model (4) but interact the exposure variable with whether the coworkers are in the same within-establishment 2004 earnings quartile as the individual. As shown in Table 7, I find that spillovers are largest amongst individuals with similar earnings. In column 2, we see that, conditional on general exposure to entrepreneurial coworkers, if *all* of an individual's entrepreneurial coworkers are also in the same within-establishment earnings quartile as them, their predicted likelihood of subsequent entrepreneurship more than doubles.[49] In other words, spillovers are amplified if an individual's entrepreneurial coworkers earn similar amounts, and thus likely work more closely, to them.

Second, I consider individuals who may be in the same social or mentorship groups and whose personal characteristics may make entrepreneurial experiences more relevant. I proxy these groups by looking at individuals within the same demographic groups, specifically women and immigrants. In addition to potentially forming the basis of social or mentor relationships, sex and immigrant status may also change the type of information that is conveyed in the spillovers. For example, female entrepreneurs may have suggestions for navigating the male-dominated sphere of entrepreneurship; immigrants (individuals born outside the U.S.) may have more experience with legal issues of being an entrepreneur while on a visa. The scope for homophilic mentorships for women is particularly large, given the literature on female mentorship.[50]

[48] In the context of human capital learning, Jarosch, Oberfield, and Rossi-Hansberg (2021) find that individuals who are younger than 40 are the most likely to learn, particularly from other young workers.

[49] The coefficient on the share of an individual's coworkers who were recently entrepreneurs is 0.024, and the coefficient on the share of their coworkers who were recently entrepreneurs *and* are in the same earnings quartile as the individual is 0.034.

[50] For example, Rocha and Van Praag (2020) document that women are more likely to become entrepreneurs after working at female-founded startups in Denmark; Field et al. (2016) find evidence that female friends can catalyze women's entrepreneurial

Furthermore, the scope for these mentorships in entrepreneurship is large, as Bosma et al. (2012) find survey evidence that entrepreneurs' role models tend to be of the same sex and nationality as them.

I investigate the roles of female entrepreneurs for women and immigrant entrepreneurs for immigrants by estimating versions of model (4) in which I interact the exposure variable with the individual's sex or immigrant status and also consider the share of coworkers who were entrepreneurs and either are women or immigrants. As shown in columns 3 and 4 of Table 7, I find that women only appear to learn from their female coworkers; in general, women are marginally less likely to become entrepreneurs after working with more entrepreneurial coworkers, but this is at least partially offset if those entrepreneurial coworkers are also women. Conditional on the share of her coworkers who were recently entrepreneurs, a woman with a one standard deviation (5.8 percentage points) higher share of coworkers who were recently entrepreneurs *and* are women is 0.31 percentage points marginally more likely to become an entrepreneur, 10.0% of the mean outcome.

For immigrants, I find a marginally higher propensity to become an entrepreneur after working with more entrepreneurial coworkers, and this is amplified if those coworkers are also immigrants, as shown in columns 5 and 6 of Table 7. Conditional on the share of their coworkers who were recently entrepreneurs, an immigrant with a one standard deviation (4.5 percentage points) higher share of coworkers who were recently entrepreneurs *and* are immigrants is 0.2 percentage points marginally more likely to become an entrepreneur, 5.1% of the mean outcome.

Taken together, the fact that spillovers are strongest amongst individuals who earn similar wages and belong to the same demographic groups, at least in terms of sex and immigrant status, suggest two conclusions. First, because these groups of individuals may interact more in the workplace, these patterns are consistent with spillovers being larger for true workplace peers. Second, these patterns suggest coworkers may be able to tailor their entrepreneurial lessons best to people like them. This latter notion may help explain the relative dearth of certain groups in entrepreneurship, such as women; if these groups benefit from learning from the entrepreneurial experiences of others like them, the lack of entrepreneurs in these groups may propagate in a vicious cycle.[51]

Previous entrepreneurship experience Lastly, I investigate whether individuals with previous entrepreneurial experience themselves experience spillovers. On the one hand, previous entrepreneurs have already demonstrated a desire or willingness to be an entrepreneur, and so they might be particularly susceptible to any lessons that entrepreneurial coworkers may convey. On the other hand, previous entrepreneurs already have entrepreneurial experience and thus may already know any of these lessons; for some, they may also already know that they do not enjoy entrepreneurship, and so will not be pushed to entrepreneurship by their coworkers.

I explore spillovers for previous entrepreneurs by estimating a version of model (4) in which I add the interaction between an individual's previous (1999-2003) entrepreneurship with the share of their coworkers who were previously entrepreneurs. As Table A.10 shows, individuals with recent entrepreneurial experience themselves have, if anything, negative extensive margin spillovers: the coefficient on the interaction is negative and larger in magnitude than the coefficient on the share by itself.

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responses to formal business training in India. Hampole, Truffa, and Wong (2021) find that random exposure to female MBA classmates predicts holding corporate leadership positions in the future for women, suggesting that female classmates facilitate both the transmission of gender-specific information and access to job referrals. See Ginther et al. (2020) for an example of the power of female mentorship in economics as a discipline.

[51] Because sorting of particular groups, such as women, into entrepreneurial firms may be less random than sorting of average individuals into entrepreneurial firms, the evidence of women learning from female entrepreneurs should not be taken as prescriptive causal evidence of what would happen if, e.g., a policy matched women together for learning opportunities.

I interpret this as evidence that previous entrepreneurs have little to learn from the average entrepreneurial coworkers.[52] I view this evidence also as a robustness check: if it were the case that entrepreneurial individuals, including those who were recently entrepreneurs, clustered at firms that promoted future entrepreneurship, such that spillovers are unrelated to coworkers directly, we might see spillover patterns for these previous entrepreneurs too. The fact that these previous entrepreneurs are not affected by spillovers reduces this identification concern.

III.7 Interpretation: Spillovers decrease cost and/or increase value of entrepreneurship

As demonstrated in Section II, the result that individuals with more entrepreneurial coworkers are more likely to become entrepreneurs themselves is consistent with several types of spillovers. On the one hand, exposure to entrepreneurial coworkers may decrease the entry cost to entrepreneurship, via the transmission of institutional knowledge or the reduction of perceived risk or shame of potential failure. On the other hand, exposure may increase the expected value of entrepreneurship, by transmitting skills or knowledge on how to start and run a successful business. In the next section, I study the characteristics of entrepreneurial firms in order to disentangle these mechanisms.

IV Intensive margin spillovers: Characteristics of entrepreneurship

The previous section argued for the presence of positive extensive margin spillovers. In this section, I turn to how exposure to entrepreneurial coworkers predicts the characteristics of an individual's future firm, if they become an entrepreneur (the *intensive margin*). I find that individuals who work with more entrepreneurial coworkers tend to start firms that are smaller, less productive, and less likely to grow and continue employing workers. However, if these entrepreneurial coworkers themselves ran larger, more productive, and/or growing firms, the individuals are more likely to start firms that too are larger, more productive, and growing. These results suggest scope for some true productivity gains via spillovers from particular entrepreneurs while indicating that the average future entrepreneur exposed to more entrepreneurial coworkers does not start a star firm.

IV.1 Empirical strategy: Leverage variation in exposure to successful entrepreneurs

In order to study the intensive margin, I estimate an OLS specification with rich controls that leverages cross-individual variation in exposure to entrepreneurial coworkers and to entrepreneurial coworkers with different entrepreneurial firm characteristics. This estimation is restricted to the set of individuals who become entrepreneurs in the near future.

For future entrepreneurs, I estimate models of the form

$$\begin{aligned}\text{Future entrepreneurial firm outcome}_{i,n,s} = \alpha &+ \beta_1 \text{Share of coworkers with entrepreneurship}_i \\ &+ \beta_2 \text{Share of coworkers with entrepreneurship with firm outcome}_i \\ &+ \mathbf{X}_{i,n,s}\delta + \xi_{i,n,s},\end{aligned} \tag{9}$$

which is identical to model (4) except that now the outcome is some outcome for the firm that individual i

[52] This evidence is consistent with survey evidence by Bosma et al. (2012), who find that experienced entrepreneurs are less likely to report using role models than new entrepreneurs.

starts in the next five years, such as the productivity or size of the firm. I include an additional explanatory variable: the share of individual i's coworkers who were both entrepreneurs between in the past five years and whose entrepreneurial firm satisfied some outcome (e.g., survived to a second year or was particularly productive). In some estimates of the model, I additionally include entrepreneurial firm industry fixed effects in order to test whether more exposed individuals simply tend to start firms in, e.g., less productive industries.

IV.2 Main results: Mixed intensive margin spillovers

Estimates from the above empirical strategy present a nuanced picture. Individuals who work with more entrepreneurial coworkers tend to start firms that are shorter-surviving and smaller. However, if these entrepreneurial coworkers themselves ran longer-surviving, larger, and/or more productive, the individuals are more likely to start firms that too are longer-surviving, larger, and more productive.

I estimate model (9) for several metrics of how "successful" firms are for the 2004 sample. I begin by considering a simple measure of firm success: survival. That is, are the firms that future entrepreneurs start more likely to continue to employ workers after entry if those entrepreneurs worked with more entrepreneurial coworkers, particularly if those entrepreneurial coworkers' firms also survived? As Table 8 shows, general exposure to more former entrepreneurs is associated with a lower likelihood of firm survival, although the coefficient is economically small.[53][54] However, exposure to former entrepreneurs whose own firms survived after entry is associated with higher likelihood of starting a firm that survives after entry, though this generally does not offset the negative effect from general exposure.[55][56]

Beyond firm survival, I explore other measures of firm success, including size, in terms of employment, payroll, and revenue, and revenue productivity. As shown in Table 9, the patterns are generally similar to those for firm survival: individuals who work with more entrepreneurs tend to start "worse" firms, unless their entrepreneurial coworkers themselves were successful. For example, in column 1 of Panel A, I find that a one standard deviation (14.7 percentage point) increase in the share of coworkers who were recently entrepreneurs predicts 5.5% lower entry year employment. Yet, as column 2 shows, this pattern is offset if the entrepreneurial coworkers ran large firms — i.e., if their entrepreneurial firms were in the top 10% of entry year log employment, amongst firms that entered in the same year and industry: conditional on general exposure to entrepreneurial coworkers, a future entrepreneur with a one standard deviation (3.8 percentage

[53] A one standard deviation (14.7 percentage point) increase in the share of coworkers with entrepreneurship is associated with a 0.14 percentage point lower likelihood of having an entrepreneurial firm that survives to a second year, a 0.17% decrease relative to the mean likelihood (column 1).

[54] As Table A.11, the estimates for firm survival are robust to the inclusion of entrepreneurial firm industry and entry year fixed effects, such that the patterns are not driven by more exposed entrepreneurs entering particular sectors or in particular years.

[55] While I provide evidence in Section III in support of interpreting the extensive margin results as causal, it is possible that the causal interpretation does not extend to the intensive margin results. Specifically, while exposure to entrepreneurs in general may be quasi-random, exposure to successful entrepreneurs may not be; for example, having productive entrepreneurs as coworkers may reflect that an individual has high latent productivity themself. However, note that my baseline regressions already control for the individuals' earnings, which should reflect some of their productivity. Additionally, I conduct robustness for these survival regressions by controlling for the individuals' firms' productivity (see columns 9 and 10 of Table A.11); if high productivity individuals and coworkers cluster at high-productivity firms, control for firm productivity should (at least partially) account for any bias generated by this clustering.

[56] It is worth noting that the effect of exposure to more successful entrepreneurial coworkers, by the metric of survival, may be conflated by the extent of interaction between the individual and their coworkers. That is, suppose an entrepreneurial coworker started a firm in the past five years that continues to employ workers several years after entry, yet they are now a worker at the current firm (unless they are the entrepreneur of the current firm). This could have two implications for the types of interactions this coworker would have with others. First, they may have only joined the firm very recently, meaning that they might have had limited interactions with others. Second, if they joined less recently, then perhaps they were less influential at their entrepreneurial firm (since they may have left it shortly after the firm entered), making them experience less informative for potential entrepreneurs.

point) higher share of coworkers who were entrepreneurs to particularly large firms has 4.3% higher entry year employment. As Panel B shows, these patterns persist with the inclusion of entrepreneurial firm industry fixed effects: individuals' future entrepreneurial success is predicted by their coworkers' success, even within the industry in which they start their firm.

Table 9 shows similar patterns for the likelihood of a future entrepreneur's firm being in the top 10% of entry year employment, payroll, and revenue, relative to firms that enter in the same year and industry (where I measure entrepreneurial coworkers' successes by analogous measures). The one exception is in terms of revenue productivity, where on its own, general exposure to entrepreneurs predicts a marginally higher probability of starting a particularly productive firm (column 9), but this appears to be driven by the particularly productive coworkers (column 10). Conditional on exposure to entrepreneurial coworkers, a future entrepreneur who works with a one standard deviation (4.5 percentage point) higher share of coworkers who were entrepreneurs at particular high-productivity firms is on average 0.6 percentage points more likely to run a particularly productive firm, a 9.9% increase relative to the mean outcome.[57]

These patterns suggest that *what* entrepreneurial coworkers teach individuals depends on the experiences of the coworkers, with successful entrepreneurs having a greater capacity to improve future entrepreneurs' prospects. In the remainder of this section, I consider additional outcomes that complement these standard measures and provide additional insight into the mechanisms of these spillovers.

Additional outcomes In Section A.III, I explore other ways in which more exposed individuals entrepreneurial firms differ, which provide some intuition for mechanisms. I find that exposure to entrepreneurial coworkers does not predict a higher likelihood of extreme success, as measured by making an initial public offering (IPO). Furthermore, exposed individuals tend to start firms that are less innovative, generating fewer patents, copyrights, and trademarks. I find that, in some cases, entrepreneurs are more likely to start firms in the sectors in which their entrepreneurial coworkers ran firms. Finally, I find that these firms of more exposed individuals tend to have less within-firm earnings inequality, operate with less structured management practices, are more often financed by the owners, and are less likely to be family-owned.

IV.3 Discussion: Entrepreneurial welfare

On average, individuals who become entrepreneurs after working with more entrepreneurial coworkers tend to start less successful firms. Beyond starting firms that are generally less successful, these individuals earn lower wages as entrepreneurs, as shown in Table A.12, regardless of their entry year or industry: a one standard deviation (14.7 percentage point) increase in the share of coworkers who were entrepreneurs predicts that a future entrepreneur's entry year earnings will be 2.3% lower.[58]

It is tempting to conclude that these individuals are making a sub-optimal decision to become an entrepreneur, and that their entrepreneurial coworkers are "leading them astray." However, it is important to remember that individuals become entrepreneurs for many reasons; for instance, some entrepreneurs simply enjoy being their own boss, so even running a less successful firm may be preferable to standard work. Furthermore, my metrics for firm success may not reflect how entrepreneurs view success; some individuals may become entrepreneurs as temporary ventures, such that they may not desire a long-surviving firm. Understanding entrepreneur welfare, like any welfare, is inherently difficult to do using administrative data,

[57]Estimates based on the revenue and productivity measures, which come from the LBD, should be interpreted with some caution, because the LBD has missing revenue data for some firms due to nonresponse or data linkage issues; additionally, the revenue data is a research dataset and may be processed further by the Census.

[58]Consistent with the prior intensive margin results, future entrepreneurs who work with more successful entrepreneurs (as measured in Table A.12 by having high entry year employment) are more likely to have higher earnings, conditional on their general exposure.

and so evaluating the individual-level welfare implications of these spillovers are beyond the scope of this paper.

IV.4 Interpretation: Nature of spillovers depend on experiences of entrepreneurial coworkers

Taken together, the extensive and intensive margin results highlight the multidimensional nature of entrepreneurial spillovers. General exposure to entrepreneurial coworkers predicts both more entrepreneurship and lower productivity; this is consistent with spillovers manifesting as lowering the entry cost to entrepreneurship through the transmission of institutional knowledge, thus shifting entrepreneurship behavior such that the marginal entrepreneur is less productive, i.e., negatively selected.

Meanwhile, exposure to more productive entrepreneurial coworkers predicts higher productivity, consistent with these more productive coworkers transmitting entrepreneurial skills that increase an individual's future entrepreneurial productivity. Because exposure to more productive entrepreneurs also tends to predict more entrepreneurship as well (Table 6), the positive intensive margin spillovers are arguably not driven by negative selection. That is, on average it is not the case that more successful entrepreneurial coworkers dissuade potential entrepreneurs who are unlikely to succeed (unlike in Lerner and Malmendier (2013)).

These results lead me to conclude that entrepreneurial spillovers are multi-dimensional. That is, *what* individuals learn from their entrepreneurial coworkers depends on *what* those coworkers have to teach: the relatively successful entrepreneurs possess teachable skills that may improve future firms' productivity, while the less successful entrepreneurs may still have institutional knowledge that reduces the entry cost to entrepreneurship without improving productivity.

V Structural model: How do spillovers aggregate?

The above empirical analysis demonstrates both the existence of entrepreneurial spillovers across coworkers and the mutli-dimensionality of these spillovers: exposure to entrepreneurial coworkers predicts future entrepreneurship, and the characteristics of this future entrepreneurship depends on the characteristics of the coworkers. While these patterns are robust and statistically significant, quantifying their importance in the aggregate is impossible without adding additional structure.

In this section, I build and estimate a structural model of entrepreneurial spillovers. I find that entrepreneurial spillovers can play a non-negligible role in determining the level of entrepreneurship in the economy: without learning, entrepreneurship would be 10% lower.

V.1 Model structure and characterization of solution

I extend the Lucas (1978) occupational choice model,[59] in which every individual chooses between wage work and entrepreneurship, to allow for entrepreneurial spillovers across coworkers.[60] While the model is simple, it embodies the intuitive trade-off between work and entrepreneurship and how entrepreneurial spillovers can affect this trade-off.

The economy consists of a positive mass I of individuals who repeatedly choose between wage work and entrepreneurship across several periods. Each period t, individual i is endowed with three characteristics: $h_{i,t}$, their productivity as a worker, i.e., human capital; $z_{i,t}$, their productivity as an entrepreneur; and $c_{i,t}$, their fixed cost to entrepreneurship. Conceptually, their productivity as an entrepreneur embodies

[59]See also Roy (1951) and Rosen (1982).

[60]This model is similar to that in Guiso, Pistaferri, and Schivardi (2020) and Guiso and Schivardi (2011), except that I focus on spillovers across coworkers, rather than locations, and abstract from physical capital.

their skills that increase the profitability of their firm if they choose to be an entrepreneur; these skills might include the ability to build and enact strong business plans and efficiently manage their employees, for instance. Meanwhile, their cost as an entrepreneur embodies the reduction to their payoff as an entrepreneur, relative to as a worker; this value may include several types of costs, including financial fixed costs (e.g., how expensive it is to rent a fixed production or retail space), logistical costs (e.g., how complicated filing government paperwork is), or mental costs (e.g., how stressful — or enjoyable — running a firm is).

Given these endowments, along with the equilibrium efficiency-unit wage w_t (described below), each individual makes their occupational choice and receives utility:

$$\begin{aligned} V(h_{i,t}, z_{i,t}, c_{i,t}; w_t) = \max_{x\in\{0,1\}} \; & (1-x)w_t h_{i,t} + x \max_H (f(z_{i,t}, H) - w_t H - c_{i,t}) \\ & + \beta(1-\xi)\mathbb{E}\big[V(h_{i,t+1}, z_{i,t+1}, c_{i,t+1}; w_{t+1}) | h_{i,t}, z_{i,t}, c_{it}, \text{coworkers}_{it}\big], \end{aligned} \tag{10}$$

where they choose between work ($x = 0$) and entrepreneurship ($x = 1$). If they choose to work, they receive earnings $w_t h_{i,t}$. If instead they choose to be an entrepreneur, they earn profits equal to revenue minus costs. Their revenue depends on both their productivity $z_{i,t}$ and optimal labor demand (H^* that solves the inner maximization in model (10), where labor is in terms of human capital); I assume that all entrepreneurs produce goods that are sold competitively at price 1 in an outside product market.[61] Their costs include both a wage bill ($w_t H^*$) and their idiosyncratic fixed cost $c_{i,t}$.[62] Individuals who choose to work are randomly allocated to entrepreneurs, according to the latter's labor demand, forming firms (and thus coworkers).

While I include a continuation value in model (10) that depends on current endowments and current coworkers (described in detail below), I assume that the individual's next period's endowments do not depend on their current choice. In other words, individuals freely make their occupational choice every period, and their choice does not affect their future endowments.[63] (Similarly, there is no saving in this model.) For completeness, each individual discounts their future payoffs by a discount factor β and the probability that they do not die/retire $(1 - \xi)$; individuals who die exit the model and are replaced by new individuals.

Endowments, however, are dynamic, as reflected in the continuation value in equation (10). At the beginning of each period, all surviving individuals draw new endowments that depend on their previous period endowments and exposure to entrepreneurs. I assume that each endowment follows an auto-regressive (AR(1)) path, with endowment-specific persistence and shocks. I augment the standard AR(1) model along two dimensions. First, endowments may depend on time-period specific, transitory common shocks; I model this as a linear time trend, reflecting the possibility of, e.g., aggregate productivity increasing over time due to increased availability of computers. Second, productivity and costs depend on the endowments of entrepreneurial coworkers that an individual meets in the workplace (details below).

Specifically, I model the endowments' laws of motion as:

[61] Alternatively, consider $z_{i,t}$ to reflect both productivity and market power that translates into prices.

[62] I choose to denote an individual's cost $c_{i,t}$ in terms of output, rather than labor, to reflect that I primarily consider these costs as fixed in the context of entrepreneurial spillovers. Namely, learning about these costs from coworkers may mean generally being inspired to become an entrepreneur or learning institutional knowledge that makes starting a firm easier in a way that is plausibly orthogonal to the size of the firm. In reality, there are likely costs that are both fixed and variable.

[63] In equilibrium, more productive entrepreneurs likely continue to choose entrepreneurship across periods, which could be interpreted as their firms being longer-surviving. Below, I focus on individuals who newly choose entrepreneurship, after working, and study firm size (payroll) as the measure of firm success.

$$
\begin{aligned}
\log(h_{i,t}) &= \gamma^h t + \epsilon^h_{i,t}, && \epsilon^h_{i,t} = \mu^h + \rho^h \epsilon^h_{i,t-1} + \eta^h_{i,t} \\
\log(z_{i,t}) &= \big(1 - \lambda^z s_{i,t-1}\big)\big(\gamma^z t + \epsilon^z_{i,t}\big) + \lambda^z s_{i,t-1}\big(\max\{\mathcal{M}(z)_{i,t-1}, \gamma^z t + \epsilon^z_{i,t}\}\big), && \epsilon^z_{i,t} = \mu^z + \rho^z \epsilon^z_{i,t-1} + \eta^z_{i,t} \\
\log(c_{i,t}) &= \big(1 - \lambda^c s_{i,t-1}\big)\big(\gamma^c t + \epsilon^c_{i,t}\big) + \lambda^c s_{i,t-1}\big(\min\{\mathcal{M}(c)_{i,t-1}, \gamma^c t + \epsilon^c_{i,t}\}\big), && \epsilon^c_{i,t} = \mu^c + \rho^c \epsilon^c_{i,t-1} + \eta^c_{i,t}
\end{aligned}
$$

where

$$
\begin{pmatrix} \eta^h_{i,t} \\ \eta^z_{i,t} \\ \eta^c_{i,t} \end{pmatrix} \sim N(M, \Sigma), \quad M = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \quad \Sigma = \begin{pmatrix} \sigma^2_h & 0 & 0 \\ 0 & \sigma^2_z & 0 \\ 0 & 0 & \sigma^2_c \end{pmatrix}, \tag{11}
$$

where for endowment e, $\gamma^e t$ reflect the transitory time effects, ρ^e reflects persistence, $\eta^e_{i,t}$ reflects the idiosyncratic shock, and μ^e is a constant.

The key innovation in this model is the presence of entrepreneurial spillovers, with productivity and cost endowments depending on an individual's exposure to entrepreneurs from whom they may learn.[64] For productivity and cost, the new endowment draws are a weighted average between the AR(1) value (with time effects) and, if it "improves" their endowment, a measure of their coworkers' endowments $\mathcal{M}(e)_{i,t-1}$, where the weight is given by the product of a learning parameter λ^e and the share of the individual's previous period coworkers who were recently (new) entrepreneurs $s_{i,t-1}$, defined below. Note that this learning is "on top of" the time effects that are common to all individuals, and thus the learning captures changes in endowments after exposure to entrepreneurial coworkers, conditional on time (and thus does not automatically drive aggregate changes in endowments).

By taking the maximum (minimum) of the coworkers' and the individuals' productivity (cost), I impose that entrepreneurial coworkers cannot "worsen" an individual's draw; this aligns with the lack of evidence that entrepreneurial coworkers dissuade entrepreneurship, as seen in Section III. Note that this asymmetry does not preclude individuals who become entrepreneurs after learning from their coworkers from being unsuccessful, as found in Section IV. Rather, unsuccessful entrepreneurs may have learned from their coworkers to lower their cost, making it worthwhile for them to become entrepreneurs, without increasing their productivity; consequently, exposure to entrepreneurial coworkers may lead less productive, and thus unsuccessful, individuals to choose entrepreneurship.

Spillovers matter more, in the sense that coworkers' entrepreneurial experience play a larger role in determining the individual's endowment, when λ^e is large and when more of the coworkers were recently entrepreneurs. With this weighting, an individual with zero exposure to recently new entrepreneurs simply draws their AR(1) value. See below for details on how $\mathcal{M}(e)_{i,t-1}$ and $s_{i,t-1}$ are calculated.

Individuals who are new to the model, either in the initial period or those who replace individuals who die, draw endowments from the stationary distribution (in the absence of learning) of endowments.[65]

Entrepreneurial spillovers I model entrepreneurial spillovers through the following. I assume that individuals (both workers and entrepreneurs) can have their productivity $z_{i,t}$ and cost $c_{i,t}$ endowment draws affected by the characteristics of their period $t-1$ coworkers who were recently entrepreneurs. To mimic the empirical analysis, I identify the set of each individual's coworkers who were new entrepreneurs sometime in

[64] These spillovers are similar to Lucas and Moll (2014), who model endogenous growth as knowledge diffusion through social interactions.

[65] I.e., new individuals draw from the stationary AR(1) distribution, with mean $\mu^x/(1-\rho^x)$ and variance $1/(1-(\rho^x)^2)var(\eta^x)$ for endowment x.

the previous 5 periods (years), where an entrepreneur is new if they were a worker in the previous period. Then, I suppose that the individual's productivity and cost depend on the productivities and costs these coworkers had when they were new entrepreneurs.

Specifically, I model learning in model (10) by first randomly[66] allocating all individuals to a firm (i.e., allocate all workers to entrepreneurs according to labor demand): for individual i (who is a worker or an entrepreneur), denote the firm to which is they are allocated in period t as $j(i,t)$. At the firm, they are exposed to a set of coworkers (who include the entrepreneur, if the individual is not themself the entrepreneur), denoted $\{i'|j(i',t) = j(i,t), i' \neq i\}$.

For each of their coworkers, I find the most recent period they were a new entrepreneur and denote this $\tilde{t}_{i'}^{\text{new}}$; if an coworker was never a new entrepreneur, set $\tilde{t}_{i'}^{\text{new}} = -\infty$. I calculate the share of their coworkers who were new entrepreneurs in at least one of the previous five periods:[67]

$$s_{i,t} = \frac{\sum_{i'|j(i',t)=j(i,t),i'\neq i} \mathbb{1}\left\{(t - \tilde{t}_{i'}^{\text{new}}) < 5\right\}}{\sum_{i'|j(i',t)=j(i,t),i'\neq i} 1}, \tag{12}$$

where $\mathbb{1}\{\cdot\}$ is an indicator function, in this case identifying coworkers who were new entrepreneurs in the past five periods. I then model that individual i's productivity and cost depend on the recent entrepreneurship of these coworkers. That is, in model (10), an individual's productivity and cost draws depend on two elements of their previous period coworkers' entrepreneurial experiences.

First, the draws depend on the share of their previous period's coworkers who were recently entrepreneurs $s_{i,t-1}$, which affects the weighting; an individual who meets more entrepreneurial coworkers in the workplace stands to learn more from these coworkers. Second, the draws depend on the endowments of these coworkers, from when they were new entrepreneurs. Specifically, set

$$\begin{aligned}
\mathcal{M}(z)_{i,t} &= \underbrace{\frac{\sum_{i|j(i',t)=j(i,t),i'\neq i,(t-\tilde{t}_{i'}^{\text{new}})<5} \log(z_{i,\tilde{t}_{i'}^{\text{new}}})}{\sum_{i|j(i',t)=j(i,t),i'\neq i,(t-\tilde{t}_{i'}^{\text{new}})<5} 1}}_{\text{mean log } z \text{ of recently new entrepreneurial coworkers}}, \\
\mathcal{M}(c)_{i,t} &= \underbrace{\frac{\sum_{i|j(i',t)=j(i,t),i'\neq i,(t-\tilde{t}_{i'}^{\text{new}})<5} \log(c_{i,\tilde{t}_{i'}^{\text{new}}})}{\sum_{i|j(i',t)=j(i,t),i'\neq i,(t-\tilde{t}_{i'}^{\text{new}})<5} 1}}_{\text{mean log } c \text{ of recently new entrepreneurial coworkers}}.
\end{aligned} \tag{13}$$

That is, an individual's productivity will be increased when they work with higher average productivity entrepreneurial coworkers, while their cost will be decreased when they work with lower average cost entrepreneurial coworkers.

Equilibrium Each period, an equilibrium consists of a wage w_t and optimal decisions $\{x_i^*\}_{i=1}^{I}$ such that the labor market clears with every individual optimizing their value. That is, the equilibrium wage solves:

[66]While in reality individuals are not randomly allocated to firms, the fact that individuals do not appear to internalize the learning opportunities (i.e., do not seek out entrepreneurial coworkers, Table A.6) makes the random allocation reasonable.

[67]I limit spillovers to those coming from coworkers who were entrepreneurs within the past five periods to mirror how I model entrepreneurship in the reduced form analyses. This limitation is consistent with only more recent entrepreneurial knowledge being relevant for future entrepreneurship (e.g., technology and legal logistics become outdated), similar to the notion of vintages of human capital in Chari and Hopenhayn (1991). I find some support of this notion empirically, as shown in Figure A.2. By limiting these spillovers, I may restrict the potential for spillovers from the most successful entrepreneurs (whose firms survive longer); however, it is worth noting that, empirically, these very successful entrepreneurs are less frequently coworkers, and so there is likely little scope for the average individual learning from very successful entrepreneurial coworkers.

$$\underbrace{\sum_{i:x^*_{i,t}(h_{i,t},z_{i,t},c_{c,t};w_t)=0} h_{i,t}}_{\text{labor supply}} = \underbrace{\sum_{i:x^*_i(h_{i,t},z_{i,t},c_{c,t};w_t)=1} H^*(z_{i,t};w_t)}_{\text{labor demand}}. \tag{14}$$

Under the equilibrium, there are two useful notions of entrepreneurship. First, there is the "total entrepreneurship" rate, i.e., the share of all individuals who optimally choose to be an entrepreneur in period t:

$$r_t = \frac{1}{I}\sum_i x^*_{i,t}. \tag{15}$$

Second, there is the "new entrepreneurship" rate, i.e., the share of all individuals who optimally choose to be an entrepreneur in period t but chose to be a worker in period $t-1$:

$$r_t^{\text{new}} = \frac{1}{I}\sum_i x^*_{i,t}(1 - x^*_{i,t-1}). \tag{16}$$

The total entrepreneurship is informative about the number of firms in the economy, while the new entrepreneurship rate is closer my empirical definition of entrepreneurship.[68]

V.2 Estimation strategy

I estimate the parameters of the model (i.e., the parameters in model (11)) via Simulated Method of Moments (SMM), treating each model period as one year. I target data moments of earnings, firm characteristics (namely payroll), and entrepreneurship, as well as the estimated entrepreneurial spillovers. I estimate the model from 1994-2013, with burn-in years 1985-1993 that allow the model to stabilize.

Model to data: Notion of entrepreneurship In order to estimate the model, I tweak my definition of entrepreneurship from that used in the reduced form sections of this paper. I use two definitions of entrepreneurship. First, an individual is an entrepreneur in general if they are the top earner at any firm. Second, an individual is a *new* entrepreneur if they are a top earner (as opposed to top 3 earner) at a new firm. This latter type of entrepreneur reflects how I treat entrepreneurship in the rest of the paper; as Tables A.13 and A.14 show, the main reduced form results are qualitatively similar under this definition.

Calibrated parameters I calibrate several parameters. First, I calibrate the death probability to $\xi = 0.0493$, to match the monthly death/birth rate of from Engbom (2019), based on the share of the U.S. labor force aged 45+ in 2016. Second, the "level" of the model is not identified, and so I normalize μ^h. Third, as already written in model (11) I assume zero covariances between endowments; this decreases the computational burden of the estimation and reflects that, cross sectionally, there is low correlation between mean earnings and entrepreneurship and mean payroll and entrepreneurship. I assume zero covariance between human capital and productivity, because while empirically it is likely that there is a nonzero covariance between human capital and productivity — and, as most recently argued by Hacamo and Kleiner (2020b), many high-human capital workers would likely be successful entrepreneurs too — this pattern exists in the

[68] My main definition of entrepreneurship, i.e., being a top three annual earner at a new firm, is different from the model's new entrepreneurship rate in two ways. First, in the model, each firm will only have one entrepreneur, rather than (up to) three; for this reason, I estimate the model below to match entrepreneurship outcomes from the data under the adapted entrepreneurship definition where I only count the top annual earner at a new firm as an entrepreneur. Second, in the data, some individuals are entrepreneurs at new, but different, firms across two periods, which would not be labeled as new entrepreneurship in the model. I abstract from this pattern in the model.

model without explicitly embedding a nonzero covariance. Because high human capital individuals tend to choose work and human capital is persistent, when we observe high human capital individuals switch from work to entrepreneurship in the model, it frequently is the case that they received large positive productivity shocks that induced the occupational shift; in this case, these previous high earners are subsequently high payroll entrepreneurs.

Target moments In order to estimate the remaining parameters, I target several moments of earnings, payroll, and entrepreneurship. Broadly, earnings moments are informative about human capital, since in the model workers with higher human capital receive higher earnings. Similarly, payroll moments are informative about productivity, since in the model entrepreneurs with higher productivity demand more labor, and thus pay higher payroll. Entrepreneurship moments are informative about the human capital, productivity, and costs together, since in the model individuals choose entrepreneurship when they have relatively low human capital, high productivity, and/or low costs.

First, from the main model sample (i.e., the aggregate data, 1994-2013), I target 1994 and 2013 mean log payroll and the (new) entrepreneurship rate. These moments are informative about the model levels (μ's) and trends (γ's) as well as the combination of equilibrium entrepreneurs (i.e., high productivity vs. low cost, σ^2's). Additionally, I target the mean-across-years variance of log earnings for workers and variance of log payroll for (all) entrepreneurs, which are informative about the variances (σ^2's). Finally, I target the persistence of log earnings for workers, log payroll for entrepreneurs, and entrepreneurship for everyone, which are informative about the persistence parameters (ρ's).

Second, from the main reduced form sample (i.e., individuals with coworkers in 2004), I target several entrepreneurial spillover regression estimates, which are most informative about the learning parameters (λ's). I target the extensive margin spillover from the regression of an individual's future (new) entrepreneurship on their exposure to entrepreneurial coworkers (i.e., column 3 of Table A.13), as well as the intensive margin spillovers from the regression of a future entrepreneur's entry log payroll on their exposure to entrepreneurial coworkers and the mean entry log payroll of those entrepreneurs (i.e., column 6 of Table A.14). Intuitively, entrepreneurs' productivity is somewhat observable, in the sense that it (should) correlate positively with payroll. Their cost, however, is not directly observable, but rather combines with their productivity to determine their entrepreneurial decision; effectively, we can think of the individuals who choose to become entrepreneurs, yet are relatively unsuccessful (low payroll), as possessing low cost, since this would justify their decision. This means that, when individuals who are exposed to more entrepreneurs, particularly unsuccessful entrepreneurs, are more likely both to become entrepreneurs and to become unsuccessful entrepreneurs, we intuit that they learned to lower their cost.

Estimation results Table 10 presents the estimated parameters, chosen by the Simulated Method of Moments to minimize the difference between the data and model moments, along with the comparison of these data and subsequent model moments.[69] As the table shows, simulations of the model with the estimated parameters produce model moments similar to the targeted empirical moments. For example, in the model, 0.59% of individuals are new entrepreneurs in 1994, while 0.54% of 1994 individuals are entrepreneurs in the data; similarly, 0.39% of model individuals are new entrepreneurs in 1994, while 0.36% of data individuals

[69]The estimation moments are based on the average of moments across 32 simulations of model (where simulations vary in the random shocks to endowments), each with 100,000 individuals; the estimated parameters are chosen to minimize the difference between the data and model moments, where I weight the moments unequally to account for scale differences (each weight is equal to the inverse squared data moment). While the traditionally optimal weights would be the inverse covariance-variance matrix of the data moments, these weights would place negligible weight on the learning moments, because these moments are estimated from smaller samples and are thus noisier; since the learning parameters are the most important parameters in the model, in terms of the subsequent counterfactual analyses below, I instead weight relative to the magnitudes of the moments.

are.

In order to further validate the estimation, I consider a non-targeted moment: the covariance of payroll and earnings. In both the data and model, I estimate the covariance between a new entrepreneur's log payroll and their previous period log earnings (when they were a worker) by regressing the log payroll on the previous year log earnings. In the data, the resulting covariance is 0.394; in the model, the value is 0.266. These similar positive covariances provide additional support of the model and estimation procedure.

Note that in order to facilitate the decline in aggregate entrepreneurship over time, the estimation results in a negative trend for productivity ($\gamma^z < 0$) and a positive trend for cost ($\gamma^c > 0$). This means that, holding all else fixed, entrepreneurship becomes less profitable and most costly over time. Intuitively, we can think of declining productivity as embodying an increasing difficulty to find original ideas and rising cost as embodying an increasing difficulty in entering a product market.[70]

V.3 Results: Without learning, entrepreneurship would be 10% lower

Table 11 presents the counterfactuals in which I remove learning by setting λ^z and/or λ^c equal to 0, starting in 1994. As shown in Panel A, on average across 1994-2013, I estimate that the entrepreneurship rate would be 10.1% lower in the absence of learning. Nearly all of this difference arises due to the absence of learning z. Effectively, this means that an individual's productivity draw is a larger determinant of their occupational choice than their cost, such that learning productivity has a larger scope for affecting aggregate entrepreneurship.

Despite these spillovers increasing entrepreneurship, they have a relatively small impact on aggregate productivity. In the absence of learning, aggregate productivity (total output divided by the sum of workers' human capital) is less than 0.1% lower (Panel A, column 2 of Table 11). As shown in columns 3, this relatively small impact is likely because learning productivity need not increase the average productivity of new entrepreneurs. Instead, in the absence of learning productivity (or cost), the mean productivity of new entrepreneurs is actually larger; intuitively, this means that productivity spillovers induce some lower-productivity individuals to opt into entrepreneurship after receiving a small increase to their productivity. This aligns with the patterns in column 4: while removing learning about cost intuitively leads to a higher average cost of new entrepreneurs, the same happens when I remove learning about productivity: without learning about productivity, the average new entrepreneur is more productive and thus crowds out would-be entrepreneurs with lower costs.

Panel B of Table 11 additionally demonstrates how entrepreneurial spillovers moderate the decline in entrepreneurship from 1994 to 2013. In the absence of learning, entrepreneurship would decline by 34% more. Here again, the spillovers to productivity matter more than the spillovers to cost, but both moderate the estimated decline. Taken together, the results of this model highlight the role for entrepreneurial spillovers: without these spillovers across coworkers, fewer individuals would choose to run their own firms.

[70] Note that I disallow any trend in human capital, so the estimated trend parameters for productivity and cost are best interpreted as trends without changes in human capital. In other words, a rise in cost could alternatively reflect a rise in human capital, i.e., the value of being a worker. Also note that, given a flat trend to human capital, we need declining productivity in order to match both a decline in entrepreneurship and effectively a flat payroll change from 1993 to 2014; if I fully generate the decline in entrepreneurship through a rising cost, the resulting selection into entrepreneurship implies a larger increase in average payroll.

VI Conclusion

Entrepreneurial spillovers exist and matter: when an individual works with more former entrepreneurs, they are more likely to become an entrepreneur themself. Furthermore, these spillovers are nuanced, as these future entrepreneurs are only predicted to become more successful entrepreneurs if they work with more successful entrepreneurial coworkers. These partial equilibrium results suggest that entrepreneurial learning may generate more, but perhaps less successful, entrepreneurs. In the model-based counterfactuals, entrepreneurial learning contributes to the aggregate entrepreneurship rate and moderates the aggregate decline in entrepreneurship, suggesting that these spillovers play non-negligible roles in determining aggregate outcomes.

References

Agarwal, Rajshree, Benjamin A Campbell, April Mitchell Franco, and Martin Ganco. 2016. "What do I take with me? The mediating effect of spin-out team size and tenure on the founder–firm performance relationship." *Academy of Management Journal* 59 (3):1060–1087.

Akcigit, Ufuk, Harun Alp, Jeremy G. Pearce, and Marta Prato. 2021. "Career Choice of Entrepreneurs, Inventors and the Rise of Firms." .

Azoulay, Pierre, Benjamin Jones, J Daniel Kim, and Javier Miranda. 2018. "Age and High-Growth Entrepreneurship." Tech. rep., National Bureau of Economic Research.

Azoulay, Pierre, Benjamin F Jones, J Daniel Kim, and Javier Miranda. 2020. "Age and high-growth entrepreneurship." *American Economic Review: Insights* 2 (1):65–82.

Babina, Tania, Paige Ouimet, and Rebecca Zarutskie. 2018. "Going Entrepreneurial? IPOs, Employee Reallocation, and New Firm Creation." .

Barlow, Richard E and Frank Proschan. 1975. "Statistical theory of reliability and life testing: probability models." Tech. rep., Florida State Univ Tallahassee.

Ben-David, Itzhak, John R Graham, and Campbell R Harvey. 2013. "Managerial miscalibration." *The Quarterly journal of economics* 128 (4):1547–1584.

Bernstein, Shai, Emanuele Colonnelli, Xavier Giroud, and Benjamin Iverson. 2019. "Bankruptcy spillovers." *Journal of Financial Economics* 133 (3):608–633.

Bernstein, Shai, Emanuele Colonnelli, Davide Malacrino, and Timothy McQuade. 2018. "Who creates new firms when local opportunities arise?" Tech. rep., National Bureau of Economic Research.

Bertrand, Marianne and Antoinette Schoar. 2003. "Managing with style: The effect of managers on firm policies." *The Quarterly journal of economics* 118 (4):1169–1208.

Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Megha Patnaik, Itay Saporta-Eksten, and John Van Reenen. 2019. "What drives differences in management practices?" *American Economic Review* 109 (5):1648–83.

Bloom, Nicholas, Scott W Ohlmacher, Cristina J Tello-Trillo, and Melanie Wallskog. 2021. "Pay, Productivity and Management." Tech. rep., National Bureau of Economic Research.

Bloom, Nicholas and John Van Reenen. 2002. "Patents, real options and firm performance." *The Economic Journal* 112 (478):C97–C116.

———. 2007. "Measuring and explaining management practices across firms and countries." *The quarterly journal of Economics* 122 (4):1351–1408.

BLS. 1997. *U.S. Bureau of Labor Statistics Handbook of Methods.*

Bosma, Niels, Jolanda Hessels, Veronique Schutjens, Mirjam Van Praag, and Ingrid Verheul. 2012. "Entrepreneurship and role models." *Journal of economic psychology* 33 (2):410–424.

Botelho, Tristan L, Daniel Fehder, and Yael Hochberg. 2021. "Innovation-Driven Entrepreneurship." .

Brau, James C and Stanley E Fawcett. 2006. "Initial public offerings: An analysis of theory and practice." *The Journal of Finance* 61 (1):399–436.

Bursztyn, Leonardo, Florian Ederer, Bruno Ferman, and Noam Yuchtman. 2014. "Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions." *Econometrica* 82 (4):1273–1301.

Caldwell, Sydnee and Nikolaj Harmon. 2019. "Outside options, bargaining, and wages: Evidence from coworker networks." *Unpublished manuscript, Univ. Copenhagen* :203–207.

Campbell, T Colin, Michael Gallmeyer, Shane A Johnson, Jessica Rutherford, and Brooke W Stanley. 2011. "CEO optimism and forced turnover." *Journal of Financial Economics* 101 (3):695–712.

Chari, Varadarajan V and Hugo Hopenhayn. 1991. "Vintage human capital, growth, and the diffusion of new technology." *Journal of political Economy* 99 (6):1142–1165.

Chatterji, Aaron, Solène Delecourt, Sharique Hasan, and Rembrand Koning. 2019. "When does advice impact startup performance?" *Strategic Management Journal* 40 (3):331–356.

Choi, Joonkyu, Nathan Goldschlag, John Haltiwanger, and J Daniel Kim. 2019. "Founding teams and startup performance." *Available at SSRN 3481850* .

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy. 2008. "The small world of investing: Board connections and mutual fund returns." *Journal of Political Economy* 116 (5):951–979.

Davis, Gerald F and Henrich R Greve. 1997. "Corporate elite networks and governance changes in the

1980s." *American journal of sociology* 103 (1):1–37.

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda. 2014. "The role of entrepreneurship in US job creation and economic dynamism." *Journal of Economic Perspectives* 28 (3):3–24.

Dillon, Eleanor W and Christopher T Stanton. 2017. "Self-employment dynamics and the returns to entrepreneurship." Tech. rep., National Bureau of Economic Research.

Djankov, Simeon, Yingyi Qian, Gérard Roland, and Ekaterina Zhuravskaya. 2006. "Entrepreneurship in China and Russia compared." *Journal of the European Economic Association* 4 (2-3):352–365.

Engbom, Niklas. 2019. "Firm and worker dynamics in an aging labor market." *unpublished paper* .

Falck, Oliver, Stephan Heblich, and Elke Luedemann. 2012. "Identity and entrepreneurship: do school peers shape entrepreneurial intentions?" *Small Business Economics* 39 (1):39–59.

Faleye, Olubunmi, Tunde Kovacs, and Anand Venkateswaran. 2014. "Do better-connected CEOs innovate more?" *Journal of Financial and Quantitative Analysis* 49 (5-6):1201–1225.

Field, Erica, Seema Jayachandran, Rohini Pande, and Natalia Rigol. 2016. "Friendship at work: Can peer effects catalyze female entrepreneurship?" *American Economic Journal: Economic Policy* 8 (2):125–53.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. 2020. "Integrated Public Use Microdata Series, Current Population Survey: Version 8.0."

Foster, Lucia and Patrice Norman. 2017. "The annual survey of entrepreneurs." *Journal of Economic and Social Measurement* 42 (3-4):199–224.

Fracassi, Cesare. 2017. "Corporate finance policies and social networks." *Management Science* 63 (8):2420–2438.

Giannetti, Mariassunta and Andrei Simonov. 2009. "Social interactions and entrepreneurial activity." *Journal of Economics & Management Strategy* 18 (3):665–709.

Ginther, Donna K, Janet M Currie, Francine D Blau, and Rachel TA Croson. 2020. "Can mentoring help female assistant professors in economics? an evaluation by randomized trial." In *AEA Papers and Proceedings*, vol. 110. 205–09.

Gompers, Paul, Josh Lerner, and David Scharfstein. 2005. "Entrepreneurial spawning: Public corporations and the genesis of new ventures, 1986 to 1999." *The journal of Finance* 60 (2):577–614.

Graham, John R, Campbell R Harvey, and Manju Puri. 2013. "Managerial attitudes and corporate actions." *Journal of financial economics* 109 (1):103–121.

Graham, Stuart JH, Robert P Merges, Pam Samuelson, and Ted Sichelman. 2009. "High technology entrepreneurs and the patent system: Results of the 2008 Berkeley patent survey." *Berkeley Technology Law Journal* :1255–1327.

Guiso, Luigi, Luigi Pistaferri, and Fabiano Schivardi. 2020. "Learning Entrepreneurship From Other Entrepreneurs?" .

Guiso, Luigi and Fabiano Schivardi. 2011. "What determines entrepreneurial clusters?" *Journal of the European economic association* 9 (1):61–86.

Hacamo, Isaac and Kristoph Kleiner. 2020a. "Confidence Spillovers in Competitive Environments: Evidence from Entrepreneurship." *Available at SSRN 3088068* .

———. 2020b. "Forced Entrepreneurs." *Kelley School of Business Research Paper* (16-48).

Hall, Bronwyn, Christian Helmers, Mark Rogers, and Vania Sena. 2014. "The choice between formal and informal intellectual property: a review." *Journal of Economic Literature* 52 (2):375–423.

Haltiwanger, John, Henry R Hyatt, Erika McEntarfer, Liliana Sousa, and Stephen Tibbets. 2014. "Firm age and size in the longitudinal employer-household dynamics data." *US Census Bureau Center for Economic Studies Paper No. CES-WP-14-16* .

Haltiwanger, John, Ron Jarmin, Robert Kulick, Javier Miranda, Veronika Penciakova, and Cristina Tello-Trillo. 2019. "Firm-level Revenue Dataset." Tech. rep.

Haltiwanger, John, Ron S Jarmin, Robert Kulick, and Javier Miranda. 2017. "1. High-Growth Young Firms." In *Measuring Entrepreneurial Businesses*. University of Chicago Press, 11–62.

Haltiwanger, John, Ron S Jarmin, and Javier Miranda. 2013. "Who creates jobs? Small versus large versus young." *Review of Economics and Statistics* 95 (2):347–361.

Hampole, Menaka, Francesca Truffa, and Ashley Wong. 2021. "Peer effects and the gender gap in corporate leadership: Evidence from MBA students." .

Hasan, Sharique and Rembrand Koning. 2019. "Prior ties and the limits of peer effects on startup team performance." *Strategic Management Journal* 40 (9):1394–1416.

Hellmann, Thomas and Manju Puri. 2002. "Venture capital and the professionalization of start-up firms: Empirical evidence." *The journal of finance* 57 (1):169–197.

Hirshleifer, David, Angie Low, and Siew Hong Teoh. 2012. "Are overconfident CEOs better innovators?" *The journal of finance* 67 (4):1457–1498.

Hong, Harrison, Jeffrey D Kubik, and Jeremy C Stein. 2005. "Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers." *The Journal of Finance* 60 (6):2801–2824.

Hopenhayn, Hugo, Julian Neira, and Rish Singhania. 2020. "From population growth to firm demographics: Implications for concentration, entrepreneurship and the labor share." Tech. rep., National Bureau of Economic Research.

Hvide, Hans K and Paul Oyer. 2018. "Dinner table human capital and entrepreneurship." Tech. rep., National Bureau of Economic Research.

Hyatt, Henry, Seth Murray, and Kristin Sandusky. 2020. "Business Income Dynamics and Labor Market Fluidity." .

Jarmin, Ron S and Javier Miranda. 2002. "The longitudinal business database." *Available at SSRN 2128793* .

Jarosch, Gregor, Ezra Oberfield, and Esteban Rossi-Hansberg. 2021. "Learning from coworkers." *Econometrica* 89 (2):647–676.

Kaehr Serra, Caroline and Jana Thiel. 2019. "Professionalizing entrepreneurial firms: Managing the challenges and outcomes of founder-CEO succession." *Strategic Entrepreneurship Journal* 13 (3):379–409.

Kaplan, Steven N, Mark M Klebanov, and Morten Sorensen. 2012. "Which CEO characteristics and abilities matter?" *The Journal of Finance* 67 (3):973–1007.

Karahan, Fatih, Benjamin Pugsley, and Ayşegül Şahin. 2019. "Demographic origins of the startup deficit." Tech. rep., National Bureau of Economic Research.

Karlan, Dean and Martin Valdivia. 2011. "Teaching entrepreneurship: Impact of business training on microfinance clients and institutions." *Review of Economics and statistics* 93 (2):510–527.

Kerr, Sari Pekkala and William R Kerr. 2017. *5. Immigrant Entrepreneurship*. University of Chicago Press.

Kerr, William R and Scott Duke Kominers. 2015. "Agglomerative forces and cluster shapes." *Review of Economics and Statistics* 97 (4):877–899.

Klenow, Peter J and Huiyu Li. 2021. "Innovative growth accounting." *NBER Macroeconomics Annual* 35 (1):245–295.

Kornfeld, Robert and Howard S. Bloom. 1999. "Measuring Program Impacts on Earnings and Employment: Do Unemployment Insurance Wage Reports from Employers Agree with Surveys of Individuals." *Journal of Labor Economics* 17 (1):168–197.

Leary, Mark T and Michael R Roberts. 2014. "Do peer firms affect corporate financial policy?" *The Journal of Finance* 69 (1):139–178.

Lerner, Josh and Ulrike Malmendier. 2013. "With a little help from my (random) friends: Success and failure in post-business school entrepreneurship." *The Review of Financial Studies* 26 (10):2411–2452.

Lindquist, Matthew J, Joeri Sol, and Mirjam Van Praag. 2015. "Why do entrepreneurial parents have entrepreneurial children?" *Journal of Labor Economics* 33 (2):269–296.

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

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

Malmendier, Ulrike, Geoffrey Tate, and Jon Yan. 2011. "Overconfidence and early-life experiences: the effect of managerial traits on corporate financial policies." *The Journal of finance* 66 (5):1687–1733.

Manski, Charles F. 1993. "Identification of endogenous social effects: The reflection problem." *The review of economic studies* 60 (3):531–542.

Nanda, Ramana and Jesper B Sørensen. 2010. "Workplace peers and entrepreneurship." *Management Science* 56 (7):1116–1126.

Rocha, Vera and Mirjam Van Praag. 2020. "Mind the gap: The role of gender in entrepreneurial career choice and social influence by founders." *Strategic Management Journal* 41 (5):841–866.

Rosen, Sherwin. 1982. "Authority, control, and the distribution of earnings." *The Bell Journal of Economics* :311–323.

Roy, Andrew Donald. 1951. "Some thoughts on the distribution of earnings." *Oxford economic papers* 3 (2):135–146.

Sacerdote, Bruce. 2014. “Experimental and quasi-experimental analysis of peer effects: two steps forward?” *Annu. Rev. Econ.* 6 (1):253–272.

Salgado, Sergio. 2020. “Technical change and entrepreneurship.” *Available at SSRN 3616568* .

Segal, Gerry, Dan Borgia, and Jerry Schoenfeld. 2005. “The motivation to become an entrepreneur.” *International journal of Entrepreneurial Behavior & research* .

Shue, Kelly. 2013. “Executive networks and firm policies: Evidence from the random assignment of MBA peers.” *The Review of Financial Studies* 26 (6):1401–1442.

Sorkin, Isaac and Melanie Wallskog. 2021. “The Slow Diffusion of Earnings Inequality.” .

Staiger, Matthew. 2020. “The Intergenerational Transmission of Employers and the Earnings of Young Workers.”

Stuart, Toby E and Waverly W Ding. 2006. “When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences.” *American journal of sociology* 112 (1):97–144.

Tello-Trillo, Cristina and Sean Streiff. 2020. “Matching Compustat Data to the Business Register 1976 - 2016.” *US Census Bureau Center for Economic Studies CES Technical Notes Series 20-07* .

Vilhuber, Lars, Kevin McKinney et al. 2014. “LEHD Infrastructure files in the Census RDC-Overview.” *Center for Economic Studies, US Census Bureau Working Papers* (14-26).

Table 1: Individuals who become entrepreneurs are different from average worker

	All Individuals			Future Entrepreneurs			T-Stat
	Mean	Std Dev	N	Mean	Std Dev	N	(4)-(1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Entrepreneurship							
Recent entrepreneur	0.034	0.180	46,680,000	0.090	0.287	1,456,000	237.0
Current entrepreneur	0.009	0.096	46,680,000	0.032	0.175	1,456,000	152.8
Future entrepreneur	0.031	0.174	46,680,000	1.000	0.000	1,456,000	38084.6
Share cow. entr.	0.034	0.095	46,680,000	0.064	0.147	1,456,000	248.0
Share cow. survived, age 2	0.029	0.093	46,680,000	0.057	0.143	1,456,000	234.9
Share cow. survived, age 5	0.021	0.083	46,680,000	0.038	0.118	1,456,000	170.4
Panel B: Demographics							
Age	39.09	11.83	46,680,000	37.39	11.00	1,456,000	-183.2
Female	0.47	0.50	46,680,000	0.41	0.49	1,456,000	-135.8
Male	0.53	0.50	46,680,000	0.59	0.49	1,456,000	135.8
Less than high school	0.12	0.32	4,234,000	0.11	0.31	125,000	-12.8
High school	0.28	0.45	4,234,000	0.25	0.44	125,000	-17.0
Some college	0.34	0.48	4,234,000	0.34	0.47	125,000	-4.3
College	0.26	0.44	4,234,000	0.30	0.46	125,000	29.3
Hispanic	0.10	0.29	36,370,000	0.09	0.29	1,129,000	-22.1
White	0.73	0.44	36,370,000	0.78	0.41	1,129,000	122.8
Black	0.10	0.30	36,370,000	0.05	0.21	1,129,000	-269.3
Native American	0.01	0.08	36,370,000	0.01	0.08	1,129,000	-19.4
Asian	0.05	0.22	36,370,000	0.07	0.25	1,129,000	60.3
Other race	0.01	0.11	36,370,000	0.01	0.11	1,129,000	-2.6
Born in the U.S.	0.82	0.39	46,680,000	0.80	0.40	1,456,000	-64.7
Born outside the U.S.	0.18	0.39	46,680,000	0.20	0.40	1,456,000	64.7
Panel C: 2004 Job Characteristics							
Annual earning	37,240	155,300	46,680,000	41,140	185,400	1,456,000	25.1
Log(annual earnings)	9.76	1.51	46,680,000	9.82	1.43	1,456,000	49.9
Years since joined firm	3.97	3.15	46,680,000	3.53	2.90	1,456,000	-182.5
Years until leave firm	3.04	3.07	46,680,000	1.58	2.02	1,456,000	-844.3
Panel D: 2004 Establishment Characteristics							
Log(employment)	5.42	2.46	46,680,000	4.08	2.35	1,456,000	-675.5
Firm age	8.95	3.25	46,680,000	7.96	3.65	1,456,000	-322.3

Note: This table presents entrepreneurial, demographic, job, and establishment characteristics for the sample of individuals age 20-64 at 2+ employment establishments in 2004 and the subsample of those who become entrepreneurs between 2005 and 2009. Recent entrepreneurship is entrepreneurship between 1999 and 2003; current entrepreneurship is entrepreneurship in 2004. "Share cow. entr." indicates the share of the individual's coworkers who were recent entrepreneurs; "Share cow. survived, age [A]" indicates the share of the individual's coworkers who were recent entrepreneurs and whose firms survived to an A-th year after entry. Demographics are only reported for individuals with non-imputed values. Note that all categories within a demographic category are mutually exclusive, e.g., Black identifies non-Hispanic Blacks. Note that the variance of log(annual earnings) is higher than what is typically found in the inequality literature because (a) I do not drop individuals earning below minimum wage, and (b) I do not drop individuals who appear at their primary firm for less than the full year.

Table 2: Previous entrepreneurs vary in success, but many entrepreneurial coworkers were unsuccessful

	Previous Entrepreneur *Coworkers*		*All* Previous Entrepreneurs	
	Mean (1)	Std Dev (2)	Mean (3)	Std Dev (4)
Entrepreneur of current firm	0.087	0.271	0.517	0.500
Firm survived to age 5	0.450	0.307	0.620	0.485
Entrepreneur at firm at age 5	0.117	0.245	0.374	0.484
Top 10% entry year employment	0.154	0.239	0.156	0.363
payroll	0.126	0.230	0.154	0.361
revenue	0.068	0.170	0.084	0.278
revenue productivity	0.051	0.135	0.063	0.242
N	36,310,000		1,573,000	

Note: This table presents entrepreneurial characteristics of individuals who became entrepreneurs between 1999 and 2003 and shows that these entrepreneurs vary in their past success, with the average set of entrepreneurial coworkers comprising relatively unsuccessful entrepreneurs who now work in other firms. Columns 1 and 2 present characteristics of entrepreneurial coworkers, for individuals in 2004 who have at least one previous entrepreneur as a coworker; specifically, these values are the summary statistics for the share of coworkers who satisfy some characteristic. Columns 3 and 4 present characteristics of all previously entrepreneur individuals; many of these individuals started their current firm. Top 10% measures are based on 90th percentile thresholds estimated at the entry year-industry (NAICS6) level.

Table 3: Extensive margin spillovers: Exposure to entrepreneurial coworkers predicts future entrepreneurship

	Dependent Variable: Entrepreneur 2005-2009							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of coworkers with entrepreneurship	0.105*** (0.0006)	0.056*** (0.001)	0.039*** (0.001)	0.038*** (0.001)	0.038*** (0.001)	0.027*** (0.001)	0.035*** (0.001)	0.025*** (0.001)
Log employment		x	x	x	x	x	x	x
Own entrepreneurship			x	x	x	x	x	x
Demographics				x	x	x	x	x
Log annual earnings					x	x	x	x
Age FE				x	x	x	x	x
Industry FE						x		x
State FE							x	x
N	46,680,000							

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence of positive extensive margins spillovers. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004. The columns gradually build up model (4), slowly adding controls as demonstrated in the table footer. Standard errors are robust and clustered at the establishment level. Mean of dependent variable: 0.031. Mean (std dev) of share of coworkers with entrepreneurship: 0.034 (0.095).

Table 4: Extensive margin spillovers are largest from establishment coworkers, rather than from other firm employees

	Dependent Variable: Entrepreneur 2005-2009								
Sample:	Main			Multi-estab.		Multi-estab.: 2+ Sectors		Multi-estab.: 2+ States	
Other-establishment coworkers:				All		Same State, Other Sector		Same Sector, Other State	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share of establishment coworkers with entrepreneurship	0.025***		0.024***	0.098***	0.092***	0.140***	0.139***	0.101***	0.097***
	(0.001)		(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.004)	(0.004)
Share of firm workers with entrepreneurship		0.026***	-0.000						
		(0.001)	(0.003)						
Share of other-establishment workers with entrepreneurship					0.010***		0.005***		0.010***
					(0.002)		(0.001)		(0.002)
Log employment	x		x	x	x	x	x	x	x
Log employment, firm		x							
Log employment, other estabs.					x		x		x
Other model (4) controls	x	x	x	x	x	x	x	x	x
Mean(dep var)		0.031		0.019		0.016		0.019	
Mean(new indep var)	0.034	0.034		0.014	0.018	0.011	0.020	0.014	0.017
Std dev(new indep var)	0.095	0.094		0.027	0.056	0.016	0.064	0.024	0.053
N		46,680,000		24,030,000		10,890,000		19,630,000	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that extensive margin spillovers are concentrated amongst workers in the *same* establishment within a firm. The table present regressions performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004 (in columns (1)-(3)) and subsamples of these individuals at multiple-establishment (SEIN) firms (in columns 4-9). The columns gradually build up models (5) in columns 1-3 and (6) in columns 4-9, where different sets of other-establishment workers are considered, with controls indicated in the footer. Additionally, all columns include the other standard controls (own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects). Standard errors are robust and clustered at the establishment (SEIN) level in all columns except (2), where they are clustered at the firm level. Note that for defining the set of establishments considered in columns 6-9, "sector" indicates 2-digit NAICS. Columns 6-7 compare an individual's establishment coworkers to employees at their firm in other establishments located in the same state, but different sector. Columns 8-9 compare an individual's establishment coworkers to employees at their firm in other establishments located in the same sector, but different state.

Table 5: Extensive margin spillovers are largest from contemporary coworkers, rather than from non-overlapping establishment employees

	Dependent Variable: Entrepreneur 2005-2009										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Individuals who join in 2004											
Share of coworkers with	0.091***		0.090***		0.088***		0.088***		0.088***		0.088***
entrepreneurship	(0.004)		(0.003)		(0.004)		(0.004)		(0.004)		(0.004)
Share of placebo coworkers with		0.019***	0.017***	0.022***	0.019***	0.028***	0.025***	0.026***	0.023***	0.028***	0.025***
entrepreneurship		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Placebo group: leavers in year		1999	1999	2000	2000	2001	2001	2002	2002	2003	2003
Model (4) controls	x	x	x	x	x	x	x	x	x	x	x
Log employment, placebo coworkers		x	x	x	x	x	x	x	x	x	x
Mean(share)	0.01745	0.02466		0.02320		0.02104		0.01984		0.01844	
Std dev(share)	0.02619	0.06714		0.06179		0.05377		0.05037		0.04746	
N						6,200,000					
Panel B: Individuals who leave in 2004											
Share of coworkers with	0.055***		0.053***		0.053***		0.054***		0.054***		0.054***
entrepreneurship	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)
Share of placebo coworkers with		0.035***	0.033***	0.035***	0.033***	0.028***	0.026***	0.025***	0.023***	0.019***	0.018***
entrepreneurship		(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Placebo group: joiners in year		2005	2005	2006	2006	2007	2007	2008	2008	2009	2009
Model (4) controls	x	x	x	x	x	x	x	x	x	x	x
Log employment, placebo coworkers		x	x	x	x	x	x	x	x	x	x
Mean(share)	0.02304	0.01863		0.01848		0.01969		0.02159		0.02255	
Std dev(share)	0.04331	0.04193		0.04236		0.04535		0.05085		0.06190	
N						5,710,000					

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that extensive margin spillovers are concentrated amongst overlapping — i.e., actual — coworkers. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments who either first join or last appear at their firm in 2004, in Panels A and B respectively. The columns estimate variants of model (7), with controls and groups of placebo coworkers indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). Standard errors are robust and clustered at the establishment level. The mean of the dependent variable is 0.02619 in Panel A and 0.03258 in Panel B.

Table 6: Entrepreneurial coworkers' success predicts future entrepreneurship

	Dependent Variable: Entrepreneur 2005-2009								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share of coworkers with entrepreneurship	0.024***		0.025***		0.025***		0.024***		0.023***
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
Share of coworkers with entr. and top 10% log(employment)		0.039***	0.021***						
		(0.002)	(0.002)						
Share of coworkers with entr. and top 10% log(payroll)				0.023***	0.004**				
				(0.002)	(0.002)				
Share of coworkers with entr. and top 10% log(revenue)						0.042***	0.024***		
						(0.002)	(0.002)		
Share of coworkers with entr. and top 10% log(revenue/employment)								0.041***	0.022***
								(0.002)	(0.002)
Model (4) controls	x	x	x	x	x	x	x	x	
Mean(share entr., top 10%)		0.005	0.005	0.005	0.005	0.003	0.003	0.002	0.002
Std dev(share entr., top 10%)		0.025	0.025	0.029	0.029	0.023	0.023	0.026	0.026
N					46,680,000				

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence of exposure to successful entrepreneurial coworkers amplifying the positive extensive margin spillovers. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments. The columns present estimates of several adaptations of model (8) with different measures of entrepreneurial coworkers' success. "Share of coworkers with entr. and top 10% log(employment)," e.g., is the share of coworkers who were recently entrepreneurs and whose entrepreneurial firms was in the top 10% of entry year log employment, amongst firms that entered in the same year and industry. Column 1 presents the main baseline results from Table 3 for comparison. The columns include controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). Standard errors are robust and clustered at the establishment level. Mean of dep var is 0.031. Mean (std dev) of share of coworkers with entrepreneurship is 0.034 (0.095).

Table 7: Extensive margin spillovers are stronger among likely peers and role models

	Dependent Variable: Entrepreneur in 2005-2009					
	(1)	(2)	(3)	(4)	(5)	(6)
Share of coworkers with entrepreneurship	0.026***	0.024***	0.035***	0.047***	0.014***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share of coworkers with entrepreneurship and in the same earnings quartile		0.034***				
		(0.002)				
Share of coworkers with entrepreneurship × Woman			-0.020***	-0.041***		
			(0.001)	(0.001)		
Share of coworkers with entrepreneurship and are women				-0.037***		
				(0.002)		
Share of coworkers with entrepreneurship and are women × Woman				0.054***		
				(0.002)		
Share of coworkers with entrepreneurship × Immigrant					0.049***	0.016***
					(0.001)	(0.002)
Share of coworkers with entrepreneurship and are immigrants						0.005**
						(0.002)
Share of coworkers with entrepreneurship and are immigrants × Immigrant						0.036**
						(0.003)
Model (4) controls	x	x	x	x	x	x
Within-establishment earnings bin FE	x	x				
Share of coworkers in within-establishment earnings quartile		x				
Share of coworkers who are women				x		
Share of coworkers who are women × Woman				x		
Share of coworkers who are immigrants						x
Share of coworkers who are immigrants × Immigrant						x
N	46,680,000					

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that extensive margin spillovers are amplified when the entrepreneurial coworkers have similar earnings or demographics as the individual. The table presents regression estimates of an adapted version of model (4) performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004, with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). This table adapts model (4) by adding the share of coworkers who are in the same within-establishment earnings quartile as the individual (columns 1 and 2); or interactions with whether the individual belongs to the given group (i.e., is a woman in columns 3 and 4 or is born outside the U.S. in columns 5 and 6; individuals without demographic information are excluded from the groups), as well as the share of coworkers who were entrepreneurs and belong to the group. Standard errors are robust and clustered at the establishment level. Mean of dep var is 0.034. Mean (std dev) of share of coworkers with entrepreneurship and in same earnings quartile is 0.006 (0.029). Mean (std dev) of share of coworkers with entrepreneurship and who are women or immigrants is 0.013 (0.058) and 0.007 (0.045), respectively.

Table 8: Entrepreneurial coworkers' firms' survival predicts future entrepreneurs' firms survival

	Dependent Variable: 2005-2009 Entrepreneurial Firm Survives to Age							
	2		3		4		5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of coworkers with entrepreneurship	-0.010***	-0.039***	-0.022***	-0.061***	-0.027***	-0.058***	-0.034***	-0.057***
	(0.003)	(0.011)	(0.003)	(0.008)	(0.003)	(0.006)	(0.003)	(0.005)
Share of coworkers with entr. and survived to age		0.031***		0.046***		0.042***		0.036***
		(0.011)		(0.008)		(0.007)		(0.006)
Model (4) controls	x	x	x	x	x	x	x	x
Mean(dep var)	0.8149	0.8149	0.6932	0.6932	0.6027	0.6027	0.5362	0.5362
Mean(share with entr. and survived to age)		0.05708		0.05043		0.04378		0.03758
Std dev(share with entr. and survived to age)		0.1434		0.1365		0.1274		0.1177
N	1,456,000							

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence of mixed intensive margin spillovers for survival that depend on the past success of the entrepreneurial coworkers. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments who become entrepreneurs between 2005 and 2009. The columns present estimates of (9) for different measures of firm survival, with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure); the covariate "Share of coworkers with entr. and survived to age" is the share of coworkers who were recently entrepreneurs and whose firm survived to the dependent variable age (i.e., age 2 in columns 1 and 2, etc.). Standard errors are robust and clustered at the establishment level. In this sample, the mean (std dev) of the share of coworkers with entrepreneurship is 0.064 (0.147). See Table A.11 for robustness to the inclusion of entrepreneurial industry and entry year fixed effects.

Table 9: Entrepreneurial coworkers' success predicts future entrepreneurs' success

	Dependent Variable: Entrepreneurial Firm Outcome									
	Entry year level		In top 10% (among firms that enter in same year and industry) of entry year							
	Log(Employment)				Log(Payroll)		Log(Revenue)		Log(Rev/Emp)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Without entrepreneurial firm industry fixed effects										
Share of coworkers with entrepreneurship	-0.381***	-0.441***	-0.088***	-0.106***	-0.080***	-0.101***	-0.022***	-0.034***	0.014***	0.003
	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share of coworkers with entr. and top 10%		1.104***		0.334***		0.238***		0.202***		0.125***
		(0.029)		(0.011)		(0.010)		(0.010)		(0.008)
Model (4) controls	x	x	x	x	x	x	x	x	x	x
Panel B: With entrepreneurial firm industry fixed effects										
Share of coworkers with entrepreneurship	-0.335***	-0.413***	-0.089***	-0.107***	-0.080***	-0.102***	-0.022***	-0.034***	0.014***	0.003*
	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share of coworkers with entr. and top 10%		1.069***		0.336***		0.282***		0.204***		0.126***
		(0.028)		(0.011)		(0.010)		(0.010)		(0.008)
Model (4) controls	x	x	x	x	x	x	x	x	x	x
Entr. industry FE	x	x	x	x	x	x	x	x	x	x
Mean(dep var)	1.928	1.928	0.168	0.168	0.164	0.164	0.083	0.083	0.057	0.057
Mean(share entr., top 10%)		0.009		0.009		0.009		0.006		0.005
Std dev(share entr., top 10%)		0.038		0.038		0.044		0.038		0.045
N	1,456,000									

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents additional evidence of intensive margin spillovers depending on the relative success of entrepreneurial coworkers. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments who become entrepreneurs between 2005 and 2009. The columns present estimates of (9) for different measures of firm success, with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure); the covariate "Share of coworkers with entr. and top 10%" is the share of coworkers who were recently entrepreneurs and whose firm was in the top 10% of firms that entered in the same year and 6-digit industry in terms of the dependent variable outcome (i.e., in column 1, this share is in terms of entry year log employment). In columns 1 and 2, the dependent variable is the entry year log employment; in the remaining columns, the dependent variables are indicators equal to 1 if the firm was in the top 10% of the listed measure, amongst firms that entered in the same year and industry, and 0 otherwise. Revenue and productivity (revenue/employment) measures are based on LBD data; if an entrepreneur's firm does not appear in the LEHD, they are coded as not being in the top 10% (although the top 10% threshold is based only on the firms with LBD data). Standard errors are robust and clustered at the establishment level. In this sample, the mean (std dev) of the share of coworkers with entrepreneurship is 0.064 (0.147).

Table 10: Estimated parameters and model fit

(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Parameter estimates					
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
μ^z	0.0054	μ^c	3.7824		
γ^z	-0.0514	γ^c	0.0473		
ρ^h	0.7929	ρ^z	0.9843	ρ^c	0.5370
λ^z	0.4517	λ^c	0.5099		
σ_h^2	0.9276	σ_z^2	0.2484	σ_c^2	0.7385

Panel B: Model fit of targeted moments		
Moment	Data	Model
1994 mean log payroll	11.51	11.48
2014 mean log payroll	11.54	11.46
1994 new entrepreneurship rate	0.0054	0.0059
2014 new entrepreneurship rate	0.0036	0.0039
Persistence of workers' log earnings	0.758	0.761
Persistence of all entrepreneurs' log payroll	0.908	0.886
Persistence of entrepreneurship	0.691	0.691
Reg coef: new entr. on coworkers' new entr.	0.021	0.017
Reg coef: new entr.'s log payroll on coworkers' new entr.	0.036	0.036
Reg coef: new entr.'s log payroll on coworkers' new entr. log payroll	-0.305	-0.272
Variance of workers' log earnings	2.225	2.320
Variance of all entrepreneurs' log payroll	2.712	2.585

Note: This table presents the estimated parameters (via SMM, Panel A) and the resulting model fit (based on the comparison of the targeted data moments to the model moments, Panel B). The estimation moments are based on the average of moments across 32 simulations of model (where simulations vary in the random shocks to endowments), each with 100,000 individuals; the estimated parameters are chosen to minimize the difference between the data and model moments, where I weight the moments unequally to account for scale differences (each weight is equal to the inverse squared data moment).

Table 11: Without learning, fewer individuals choose entrepreneurship

	(1)	(2)	(3)	(4)
Panel A: Average outcomes relative to estimated (with learning) values				
	Entrepreneurship rate	Aggregate productivity	Mean log(z) (new entr.)	Mean log(c) (new entr.)
Estimated	100%	100%	100%	100%
No z or c learning	89.89%	99.97%	100.4%	100.3%
No z learning	90.29%	100.1%	100.3%	100.2%
No c learning	99.68%	100.4%	100.0%	100.1%
Panel B: Trend in entrepreneurship, with and without learning				
	1994 rate	2013 rate	Change	Share of estimated change
Estimated	0.0059	0.0039	-33.25%	100%
No z or c learning	0.0059	0.0033	-44.56%	134.0%
No z learning	0.0059	0.0033	-43.69%	131.4%
No c learning	0.0059	0.0037	-36.44%	109.6%

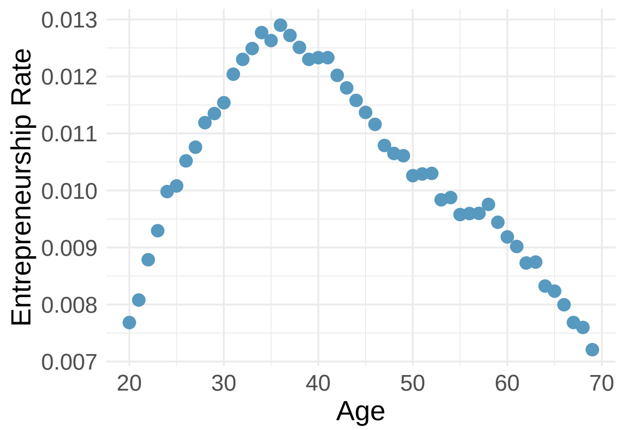
Note: This table demonstrates how learning from entrepreneurial coworkers can affect aggregate entrepreneurship, productivity, and the characteristics of entrepreneurs.

The table presents results from comparing the estimated model with counterfactual simulations in which I "turn off" learning in z and/or c. To simulate these counterfactuals, I maintain learning within the burn-in (pre-1994) periods, in order to have the same 1993 values, and then set λ^z and/or λ^c equal to 0 from 1994-2013. For the estimated model and the simulated counterfacutals, the values are based on the average of moments across 16 simulations of model (where simulations vary in the random shocks to endowments), each with 100,000 individuals.

Panel A demonstrates how learning z and c from coworkers contributes, on average, to several outcomes. The panel presents the mean counterfactual value divided by the estimated value for several outcomes, across 1994-2013. Entrepreneurship rate refers to the "new" entrepreneurship rate, i.e., the share of individuals who are entrepreneurs in a given period but were workers in the previous period. Aggregate productivity is aggregate output (summed across all firms) divided by aggregate labor supply (measured in human capital, summed across all workers). Mean log(z) and mean log(c) are the average log productivity and cost, respectively, of new entrepreneurs.

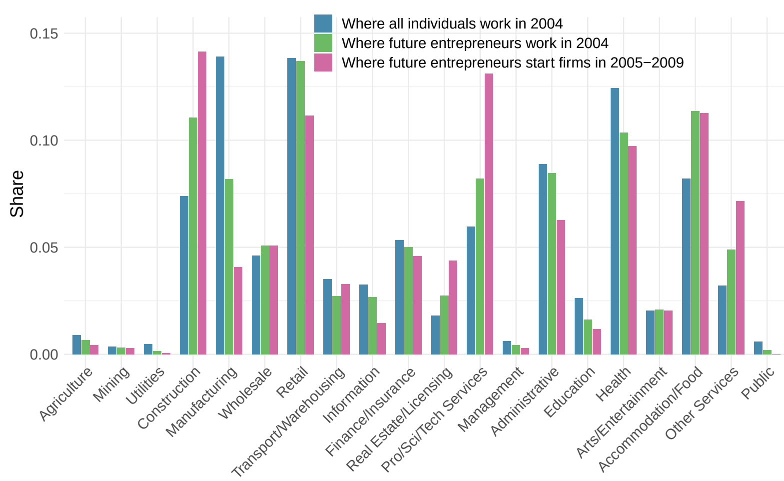
Panel B demonstrates how learning z and c from coworkers contributes to the decline in entrepreneurship. Columns 1 and 2 show the (new) entrepreneurship rate in 1994 and 2013, in the model; column 3 shows the percent change from 1994 to 2013, given the learning. Column 4 divides the changes by the estimated change (with learning both z and c).

Figure 1: Entrepreneurship has inverse-U relationship with individual age



Note: This figure presents the entrepreneurship rate by age, for all (working) individuals age 20-69 in 2004. Entrepreneurship rates are concave in age, with individuals in their 30's have the highest rate.

Figure 2: Entrepreneurial individuals work and start firms across the economy

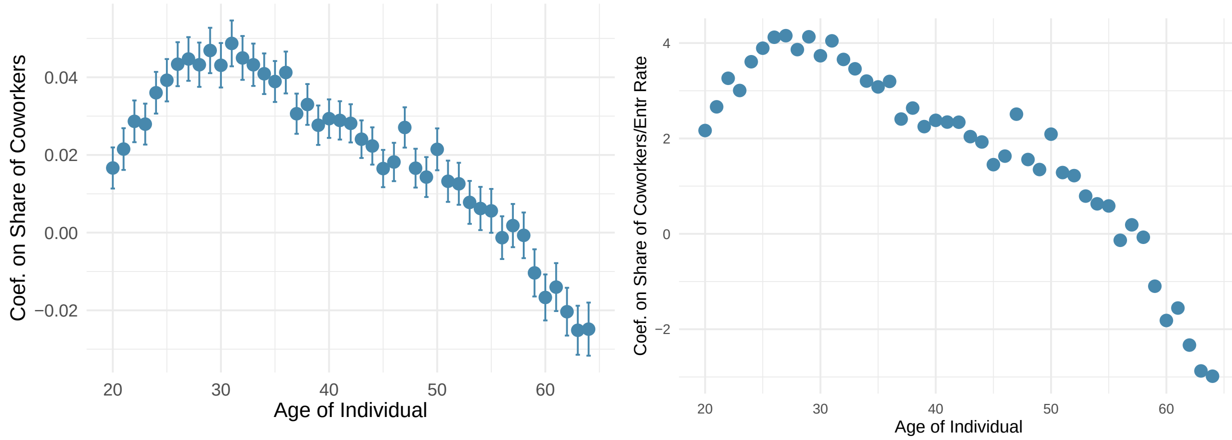


Note: This figure plots the distributions of sectors of 2004 primary firms for all individuals and for future (2005-2009) entrepreneurs, as well as the distribution of sectors in which the future entrepreneurs start firms. The NAICS codes map to sectors as follows (note that some sector names are abbreviated in the figure): 11: Agriculture, Forestry, Fishing and Hunting; 21: Mining, Quarrying, and Oil and Gas Extraction; 22: Utilities; 23: Construction; 31-33: Manufacturing; 42: Wholesale Trade; 44-45: Retail Trade; 48-49: Transportation and Warehousing; 51: Information; 52: Finance and Insurance; 53: Real Estate and Rental and Leasing; 54: Professional, Scientific, and Technical Services; 55: Management of Companies and Enterprises; 56: Administrative and Support and Waste Management and Remediation Services; 61: Educational Services; 62: Health Care and Social Assistance; 71: Arts, Entertainment, and Recreation; 72: Accommodation and Food Services; 81: Other Services (except Public Administration); 91: Public Administration.

Figure 3: Extensive margin spillovers are inverse-U shaped in individual's age

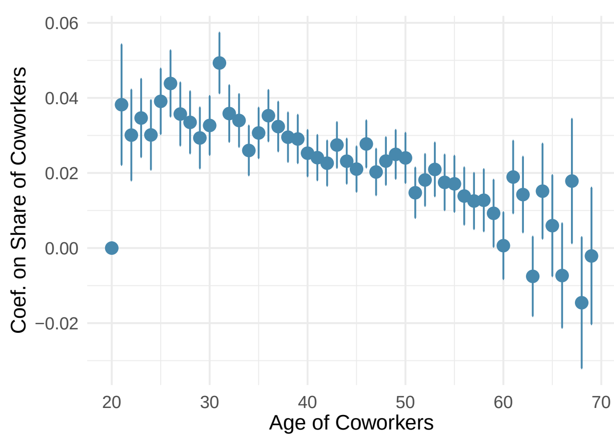
(a) Coefficients by age

(b) Coefficients by age divided by entrepreneurship rate by age



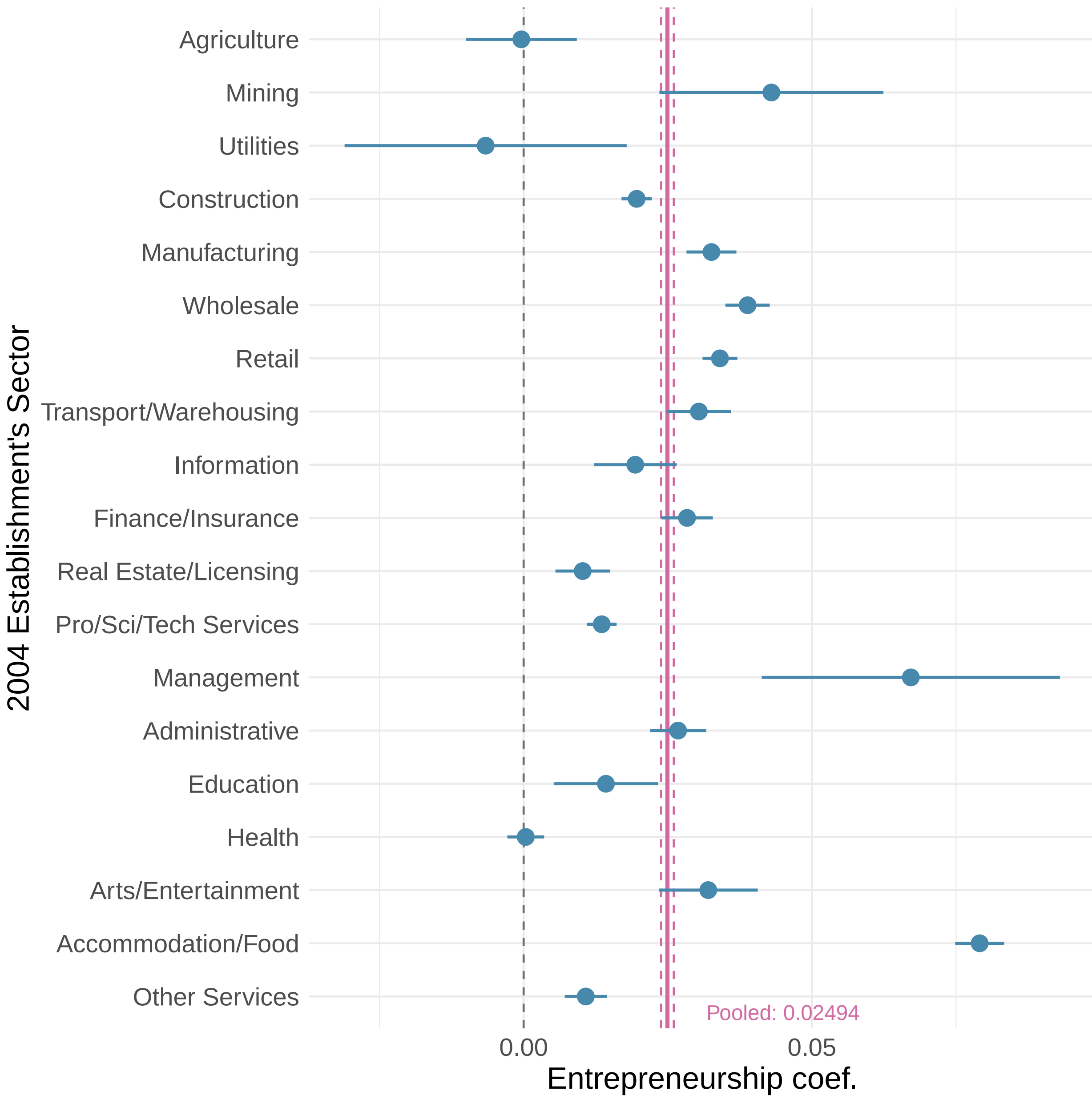
Note: This figure presents evidence that extensive margin spillovers are largest for young and middle aged individuals and non-exist (or even negative) for older individuals. This figure presents coefficient and 95% confidence interval estimates of model (4), modified by interacting the share of coworkers who were recently entrepreneurs with the individual's age. The figure plots the coefficients on the share of an individual's coworkers who were entrepreneurs between 1999 and 2004 by the age of the individual. Panel A presents the raw coefficients, while Panel B normalizes these coefficients by the age-specific entrepreneurship rate (see Figure 1) Standard errors are robust and clustered at the establishment level.

Figure 4: Extensive margin spillovers are highest from younger coworkers



Note: This figure shows evidence that extensive margin spillovers are stronger when the entrepreneurial coworkers are younger. The figure presents coefficient and 95% confidence interval estimates of model (4), modified by separating out the share of coworkers who were recently entrepreneurs by the age of the coworkers (and controlling for the share of coworkers who are each age). The figure plots coefficients on the share of an individual's coworkers who are both a given age and were entrepreneurs between 1999 and 2004. Standard errors are robust and clustered at the establishment level.

Figure 5: Entrepreneurial spillovers vary by sector



Note: This figure presents evidence that extensive margin spillovers exist in most sectors of the economy. The figure presents regression coefficient and 95% confidence interval estimates of an adapted version of model (4), performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004, in which I replace the explanatory variable (share of coworkers who were entrepreneurs in the past 5 years) with the share of coworkers who were entrepreneurs in the past 5 years interacted with the sector of the 2004 establishment (SEIN). I exclude the coefficient for workers in the public sector here, who account for less than 0.5% of the sample, whose coefficient is substantially different and very noisy (coefficient −0.3163, standard error 0.010). See Figure 2 for NAICS codes of each sector.

Appendix

A.I Data appendix

In this section, I present additional details on how I construct several variables from U.S. Census Bureau datasets, which are described with fewer details in Section I. This section is organized around each dataset.

A.I.1 Longitudinal Employer Household Dynamics (LEHD)

The LEHD is the crucial source of data for this paper, as I use the LEHD both to identify entrepreneurs and to connect individuals with their coworkers.

The LEHD is constructed from firm-side state unemployment insurance (UI) records. It contains quarterly information on employment and earnings for most individuals within a state, with longitudinal employer and individual identifiers that can be followed across states. These longitudinal identifiers allow me to track the entrepreneurial outcomes of individuals and their coworkers over time. I use LEHD data from 1993 to 2013 for a balanced sample of 18 states.[71]

The LEHD contains information on earnings and demographics. The earnings include salaries and wages as well as bonuses, stock options, and other cash pay, allowing me to find top (labor income) at each firm; this allows me to identify entrepreneurs as top earners. I use the CPI-U from the Bureau of Labor Statistics (BLS) to deflate earnings measures to 2010 dollars. The LEHD also contains demographic information for individuals, including date of birth, sex, race/ethnicity, education, and country of birth, which allows me to explore the heterogeneity of entrepreneurial spillovers.[72] I define an individual's age in a year as the difference between the year and the individual's year of birth (such that their age is their age on December 31st of that year) and restrict to individuals aged 20-69.

Using the LEHD, I study employers at two levels of aggregation. First, the least aggregated firm unit with known employees within the LEHD is a state-level unemployment insurance account (called a State Employer Identification Number, or SEIN).[73] I refer to this unit as an **establishment**, but note that this unit can contain multiple physical establishments of a single firm within a given state. That is, an SEIN is a tax ID number that pools together physical establishments of a firm within a given state, generally within a given sector. I primarily study individuals and their coworkers (i.e., other workers) at the SEIN level, since I assume that individuals have the most contact within their firm with coworkers at the same SEIN. Second, for my measures of firm outcomes (and robustness for coworkers), I study firms, pooling across states and sectors. That is, a **firm** consists of all establishments belonging to the same national firm, within my sample of states.[74] Note that for firms that only exist in my sample of states, my measure of a firm captures the entire firm; for firms that exist in states outside of my sample, my measure of a firm will only capture part of the firm.

The LEHD provides detailed information on the industry of each establishment, which is useful both for controlling for industry patterns to entrepreneurship and to exploring heterogeneity and mechanisms. I use the 6-digit NAICS codes [75] to group establishments by industry. For each firm, I assign the sector

[71] This results in a balanced panel of the following 18 states: AK, AZ, CA, CO, FL, ID, IL, IN, KS, LA, MD, MO MT, NC, OR, WA, WI, WY. In 2013, these states account for 43.0% of total (pay period including March 12) employment, 44.8% of firms, and 44.4% of establishments in the U.S. (50 states and D.C.), estimated using the Business Dynamics Statistics dataset (the public tabulations of the U.S. Census Bureaus' Longitudinal Business Database). Other states have incomplete or fluctuating coverage over this time period and so are excluded in order to create a balanced panel of states; the LEHD does have data in previous years for a handful of states, but I choose to start in 1993 in order to get as many states as I can while still maintaining a long panel.

[72] The demographic information is drawn from other Census and government datasets, mostly the Decennial Censuses and the Social Security Administration's Numident file. Coverage is imperfect, and while the Census does impute missing values, I only use variation from the non-imputed values.

[73] Note that the U.S. Census Bureau assigns individuals within an SEIN to distinct locations, called SEIN-units; this is an imputation and thus cannot be reliably used to study spillovers across coworkers.

[74] That is, I combine all SEINs that map to the national Census variable FIRMID, using the LEHD's ECFT26 crosswalk. The FIRMID variable allows me to connect individuals in the LEHD to firm outcomes in the remaining datasets.

[75] I use the 2012 "FNL" NAICS codes that source industry information from both the Covered Employment and Wages program and the LBD (Vilhuber, McKinney et al. (2014)). 6-digit NAICS codes are the most disaggregated industry codes available and are quite narrow. For example, NAICS 311111 consists of firms that manufacture dog and cat food, while NAICS 311119 consists of firms that manufacture food for other animals; and NAICS 441110 consists of automobile dealers that sell new cars, while NAICS 441120 consists of dealers that sell used cars.

(approximately 2-digit NAICS codes) with the majority of employees, summing across establishments.

The LEHD covers almost all sectors of the economy, making it an ideal source for studying entrepreneurial spillovers in a broad context and sectoral heterogeneity. Namely, it includes workers covered by the UI system (i.e., workers who could claim UI benefits if they experience an eligible dismissal from their employer); in 1994, this mass of workers reflected about 96% of employment and 92.5% of wages and salaries (BLS (1997, pg. 42)). Due to the nature of the UI system, the data does not include small non-profits, self-employed workers, some agricultural workers, and federal government worker.[76] Note that this nature of the LEHD means that some firm owners, especially sole proprietors, are not covered by the LEHD because they do not take labor income earnings (Hyatt, Murray, and Sandusky (2020)); I discuss how this affects my definition of entrepreneurship in Section I.

For each individual, I define a **primary firm** and **primary establishment** for each year. An individual's primary firm is the firm from which they earn the most in the year (summing across all establishments) and thus at which they presumably spend the most time; their primary establishment is the establishment at their primary firm at which they earn the most in the year. Below, I measure characteristics of an individual's **coworkers**, who are other workers at the individual's primary establishment in a given year, for whom the establishment is also their primary establishment.

In an attempt to assess the quality of firms, I measure several outcomes in the LEHD. I proxy firm survival by tracking whether a new firm continues to employ individuals in the years after it enters; e.g., a firm survives to a second year if it employs individuals (counting all earners at the firm, regardless of whether the firm is the earners' primary firm, in my sample of states) in the year after it enters.[77] I also measure total employment and payroll levels and growth, including all individuals who have earnings at a firm in a given year (i.e., not restricting to individuals for whom the firm is their primary firm). Finally, I flag firms that are particularly large or fast-growing, by identifying firms whose employment levels or growth fall in the top 10% of the given measure among firms that entered in the same year, in the same (6-digit NAICS) industry.

Measuring entrepreneurship While there are several ways of measuring entrepreneurship, I follow the recent literature and call an individual an entrepreneur if they are a top three earner at a new firm, although I conduct a variety of robustness and audit checks on this definition. This measure of entrepreneurship captures individuals who likely hold influential positions at young firms.

In this paper, I consider a broad notion of entrepreneurship. I am interested in the founding of firms, so I take an "initial team" approach to defining and measuring entrepreneurship. That is, I call an individual an entrepreneur if they are amongst the three highest paid employees of firm in the first year that the firm has paid employees.[78]

In order to enact this definition, I determine the year in which a firm enters. I follow the literature and start by finding the first year a firm has positive employment in the national LBD, i.e., the first year the firm's oldest establishment has employment in the payroll period that contains March 12 (Haltiwanger, Jarmin, and Miranda (2013, pg. 353)).[79] I use this first year as each firm's **entry year**, with minor adjustments. First, some firms, particularly small and new ones, appear in the LEHD without appearing the LBD. Second, some firms appear in the LEHD years before or after they first appear in the LBD.[80] For firms in either of these two cases, I take the first year that the firm appears with employment in the LEHD (in my sample of states)

[76] For details, see Kornfeld and Bloom (1999, pg. 173), BLS (1997, pg. 43) and `http://workforcesecurity.doleta.gov/unemploy/pdf/uilawcompar/2012/coverage.pdf`.

[77] In some cases, firms "dip in and out" of employment within the LEHD, such that a firm may appear to not survive to the second year after entry but then reappears in the third year after entry.

[78] I follow Agarwal et al. (2016), Kerr and Kerr (2017), and Azoulay et al. (2018) in doing this; Azoulay et al. (2018) audits this initial team definition using W-2 records to compare founders to initial team members. They find that "90% of the owner-workers are in fact among the top three earners in the firm during the first year," though this coverage is noisy.

[79] Note that the LBD begins in 1976, such that firm entry years are left censored in 1976. I focus on entrepreneurship, and thus firm entry, between 1994 and 2013, so this censorship is not relevant.

[80] A firm may appear in the LEHD before it appears in the LBD because of the structure of the LBD: because LBD employment is based on the payroll period that contains March 12, firms that enter after that payroll period will appear in the LEHD but only appear in the LBD in the following year (if they survive). A firm may appear in the LEHD after it appears in the LBD for several reasons. First, firms only appear in the LEHD if they pay unemployment insurance taxes, which may not be relevant to all, especially younger, firms in the LBD. Second, because my LEHD sample contains an subsample of all states, it is possible for firms to appear in the LEHD, in my sample of states, after they appear in the LBD and in states outside my sample.

as its entry year.[81] Finally, while the firm identifiers are longitudinal, it is possible (but uncommon) for firm IDs to change over time. Because I am interested in new firms, rather than, e.g., firms that have changed ownership, I attempt to avoid misclassifying firm ID changes as new firms by ignoring in my definition of entrepreneurship below firms that are very large in their entry year,[82] who I assume are less likely to be truly new firms.[83]

Given a firm's entry year, I identify the "initial team" of the firm as the individuals with the three highest annual earnings in the firm in the entry year. Unless otherwise noted, I call an individual an **entrepreneur** in a given year if they are one of the top three highest paid employees of a firm and the year is the firm's entry year.[84][85]

This notion of an entrepreneur is intended to capture an individual who most likely is integral to or closely witnesses the decision-making at a young firm, regardless of whether they are a legal owner or founder of the firm. There are two important aspects to consider for interpreting this definition. First, my definition of a firm's entry year marks the first year it has paid employees. Firms may have existed previously without employees, such that the entry year likely lags the initial planning and starting of a firm. Nonetheless, the transition to being a firm with paid employees is an extremely important step in a firm's life, particularly for firms that hope to grow.

Second, my definition *will not* pick up "owner-investors," who take their payoffs in the form of profit dividends rather than in wages (and thus would not appear in the LEHD). This is particularly relevant for sole proprietorships and partnerships, for which owners are not supposed to take wages, and thus should not appear in the LEHD (Hyatt, Murray, and Sandusky (2020)). I take any distinction between entrepreneurs, "owner-workers," managers, "firm-runners," etc. to be semantics alone; put differently, as discussed below, what matters for coworker learning is experience as part of a firm when the firm is very young, rather than strictly investment or idea-generation experience. I further conduct a robustness exercise by separately analyzing entrepreneurs at corporations, vs. those at sole proprietorships or partnerships, since the individuals I identify as entrepreneurs at corporations are more likely to be the true owners and founders of their companies.[86]

Finally, note that for my analysis of spillovers, an individual is only identified an entrepreneur in their firm's entry year; they are also always considered a worker, regardless of their entrepreneur status.

Entrepreneurial outcome in the LEHD I measure absolute firm size in terms of employment and payroll from the LEHD, counting all individuals with employment at a firm in a year (i.e., not restricting to individuals for whom the firm is their primary firm). I also measure relative firm size by identifying firms whose LEHD employment or payroll falls in the top 10% among firms that enter in the same year and (6-digit NAICS) industry. Note that the thresholds determining which firms are in the top 10% of a given

[81] In order to avoid misclassifying old firms that are simply entering the my sample of states in the LEHD as new firms, I ignore in my definition of entrepreneurship below any firm that appears in the LEHD strictly more than two years after its first year in the LBD.

[82] I.e., firms whose entry year LEHD employment exceeds the 99th percentile of employment (slightly under 200 employees) for all entering firms.

[83] An alternative method to determine a firm's entry year without the LBD is to use the firm age variable as listed in the LEHD (as described in Haltiwanger et al. (2014)). This variable is based on several sources, mostly the LBD and the National Employer Characteristics File (NECF), and is meant to provide age information for all firms in the LEHD (note that while the majority of the LEHD establishments can be mapped to the LBD, where firm age has been traditionally measured, this mapping is biased: smaller, younger firms are less likely to be matched). I conduct a robustness analysis, defining entrepreneurship using the LEHD firm age variable, where I identify a firm's entry year by the year in which the firm is aged 0 (note that the Census zero-indexes age, while I one-index age). The results, shown in column 2 of Table A.13 are virtually the same as my main extensive margin results: a one standard deviation (8.8 percentage points) increase in the share predicts a 0.22 percentage point higher likelihood of future entrepreneurship, 8.5% of the mean outcome.

[84] Note that this firm need not be the entrepreneur's primary firm in the year and that not all firms have three entrepreneurs. For a more restricted definition, I consider only the top earner at new firms, which yields similar results, as shown in Table A.13: a one standard deviation (5.9 percentage point) in the share of coworkers who were recently the top earner at a new firm predicts a 0.13 percentage point higher likelihood of becoming a top earner at a new firm in the next five years, 9.13% of the mean outcome. I similarly investigate and find qualitatively similar intensive margin results using this definition, as shown in Table A.14.

[85] In my structural model I only consider top paid employees as entrepreneurs; see Section V for details.

[86] See columns 4-7 of Table A.13, which show my main extensive margin results if I only consider each legal type, in turn. As column 4 shows, I still find a positive coefficient on the share of an individuals' coworkers who were recently entrepreneurs, if I restrict my definition of entrepreneurship (for both dependent and independent variables) to corporations. For corporations, I find that a one standard deviation (8.3 percentage points) increase in the share predicts a 0.12 percentage point higher likelihood of future (corporation) entrepreneurship, 5.7% of the mean outcome.

outcome are based on all firms that start in a given year, not restricting to firms started by individuals in my main reduced form sample; the thresholds are also calculated by weighting firms equally, rather than by weighting firms by the number of entrepreneurs (up to three). In practice, this means that more than 10% of previous entrepreneurs started firms with top 10%.

I measure firm survival and entrepreneur retention using the LEHD. I define a firm's survival to a given firm age based on whether the firm has nonzero employment at that age and say that, e.g., a firm survives to age 2 if it employs workers in its second year. In this paper, I consider survival as a marker of success — more successful firms survive for more years; I abstract from the possibility of successful exits (e.g., mergers and acquisitions). I measure whether an entrepreneur is still employed at their entrepreneurial firm at a given firm age (regardless of whether the firm is their primary firm).

A.I.2 Longitudinal Business Database (LBD)

I use the Longitudinal Business Database (LBD) to construct my definition of entrepreneurship, as described in Section I.2. The LBD starts in 1976 and tracks all U.S. business establishments and firms with paid employees over time, including physical establishments in states not covered by the LEHD in early years.[87]I aggregate the LBD to the firm-level.[88]

A.I.3 LBD revenue and productivity

The LBD provides information on national firm-level revenue and employment for larger employers in the U.S. beginning in 1997, allowing me to study firm revenue productivity (Haltiwanger et al. (2017)).[89] Note that this data is available to researchers on approved projects through the Federal Statistical Research Data Center (FSRDC) network, where additional documentation is available (Haltiwanger et al. (2019)).

This dataset is relatively new and marks a vast improvement to researchers' abilities to measure firm output, as previously most U.S. research was restricted by administrative data availability to studying productivity in only the manufacturing sector (using the U.S. Census Bureaus' Census of Manufactures). However, this dataset is not currently comprehensive of all firms in the U.S. but rather is potentially biased in its coverage towards larger firms, which are more likely to be covered in the source data (Haltiwanger et al. (2017)). Thus, my analysis on productivity outcomes comes with the caveat that these outcomes are sometimes unavailable for small (and often young) firms.

I consider one main measure of firm-level revenue productivity. I measure revenue productivity as log real revenue per worker, using both the LBD information on revenue and employment; I use the CPI-U from the BLS to deflate the revenue measure to 2010 dollars. In addition, in unreported analysis, I measure within-industry variation in productivity by demeaning the latter measure at the 6-digit NAICS level, using the firm-level industry codes in the LBD.[90] The regression estimates are very similar when measuring productivity the two different ways, largely due to the inclusion of industry fixed effects in regressions, and so I do not report the second measure.

A.I.4 Annual Survey of Entrepreneurs (ASE)

The ASE collects information from firms' owners on a variety of outcomes which are useful for studying the mechanisms of entrepreneurial spillovers.

This dataset is a firm-level survey based on collaboration of the Census with the Ewing Marion Kauffman Foundation and the Minority Business Development Agency.[91][92] The ASE ran annually to collect 2014, 2015, and 2016 economic and demographic data on businesses and owners for a representative sample of non-farm businesses with paid employees and with receipts of at least $1,000.

I use the ASE in two ways. First, I consider owner-level information by connecting entrepreneurs in the LEHD to owners in the ASE. Unfortunately, the ASE contains limited person identifiers for owners, so I

[87]For details, see Jarmin and Miranda (2002).

[88]I do this by aggregating across physical establishments with the same FIRMID variable value.

[89]This data is at the FIRMID-level.

[90]That is, I industry-adjust the productivity measure by subtracting from a firm's log(revenue/employment) the firm-weighted industry average log(revenue/employment), where revenue, employment, and industry are all sourced from the LBD.

[91]For details, see Foster and Norman (2017) and https://www.census.gov/programs-surveys/ase/about.html.

[92]This data is at the FIRMID-level.

match entrepreneurs to owners using demographics.[93] All three years of the ASE collect coarse demographic information for up to four owners for each firm. For entrepreneurs that I can match to owners, I study the owner-level ASE information. Namely, I use a survey question on why these owners founded the business (if they founded it). See Section III.3 for details.

Second, I consider firm-level information to study several firm characteristics. This includes information on how the firms are managed and financed, whether they are family-owned, and whether they engage in innovative behavior.[94]

I construct several outcome variables for entrepreneurs and their entrepreneurial firms using the ASE. Here, I present the survey questions and how I construct each variable. For original worksheets, see `https://www.census.gov/programs-surveys/ase/technical-documentation/questionnaires.2014.html`.

Role models The 2014-2016 ASE waves ask each of up to four owners why they own the business. I use this information to identify entrepreneurs who cite other entrepreneurs as serving as role models for them.

Specifically, the survey asks, "How important to Owner 1 are each of the following reasons for owning this business?" (and the same for Owners 2, 3, and 4). The survey then provides several options, as follows below, and asks the owner to mark whether each option was "Not Important," "Somewhat Important," or "Very important:"

- Wanted to be my own boss
- Flexible hours
- Balance work and family
- Opportunity for greater income/Wanted to build wealth
- Best avenue for my ideas/goods/services
- Couldn't find a job/Unable to find employment
- Working for someone else didn't appeal to me
- Always wanted to start my own business
- An entrepreneurial friend or family member was a role model
- Other

I focus on the second to last option, and say that an entrepreneur cites role models as being very important to them if they answer "Very Important," and as being at least somewhat important to them if they answer "Somewhat Important" or "Very Important."

Management variables The 2015 ASE includes seven questions on firms' management practices. These questions are based on the management questions in the MOPS. For each question, I follow past literature using the MOPS data and normalize each answer to take values between 0 and 1, where zero corresponds to the least structured practices (i.e., practices that are less explicit, formal, frequent, or specific) and one corresponds to the most structured practices (Bloom et al. (2019)). These questions can be divided into two categories: questions on how firms monitor and set targets for production and questions on how firms incentivize their workers.

Based on these questions, I create three ASE management measures: a measure of total management structure (the average of all seven questions, after normalization), a measure of monitoring and targeting (the average of the monitoring and targeting questions), and a measure of incentives (the average of the incentives questions). These questions (with some abbreviations), and the normalizations, are provided below in Table A.1.

[93] The 2016 ASE contains person-identifies for a small share of firms. To the best of my knowledge, these identifies are sourced from the Business Register (BR), which has person-identifies for sole proprietorships. Because owners of sole proprietorships should not take wage and salary earnings, they should not appear as entrepreneurs in the LEHD (Hyatt, Murray, and Sandusky (2020)). This means that these identifiers are not useful for linking my entrepreneurs to ASE owners.

[94] The management information is based on questions only available in the 2015 wave of the ASE; the other information is based on questions available in all waves.

Table A.1: 2015 ASE management questions

Question text	Answer text	Value
Panel A: Monitoring and targeting questions		
What best describes what happened at this business when a service or production problem arose?	No action was taken	0
	We fixed it but did not take further action	1/3
	We fixed it and took action to make sure that it did not happen again	2/3
	We fixed it and took action to make sure that it did not happen again, and had a continuous improvement process to anticipate problems like these in advance	1
How many key performance indicators were monitored at this business?	No key performance indicators	0
	1-2 key performance indicators	1/3
	3-9 key performance indicators	2/3
	10 or more key performance indicators	1
How frequently were the key performance indicators reviewed at this business?	Never	0
	Yearly	1/6
	Quarterly	1/3
	Monthly	1/2
	Weekly	2/3
	Daily	5/6
	Hourly	1
What best describes the time frame of business, service, or production targets at this business?	No targets	0
	Main focus was on short term (less than one year) targets	1/3
	Main focus was on long term (more than one year) targets	2/3
	Combination of short-term and long-term targets	1
How easy or difficult would it have been to achieve business, service, or production targets at this business?	Minimal effort	0
	Extraordinary effort	1/4
	Less than normal effort	1/2
	Normal effort	3/4
	More than normal effort	1
Panel B: Incentives questions		
What was the primary way employees were promoted at this business?	Employees are not normally promoted	0
	Promotions were based mainly on factors other than performance and ability	1/3
	Promotions were based partly on performance and ability and partly on other factors	2/3
	Promotions were based solely on performance and ability	1
When was an under-performing employee reassigned or dismissed?	Under-performing employees are not normally reassigned or dismissed	0
	After 6 months of identifying employee under-performance	1/2
	Within 6 months of identifying employee under-performance	1

Other outcomes The 2014-2016 ASE waves all containing information on financing, whether firms are family-owned, and whether firms engage in innovative behavior. These outcomes are based on the following questions:

1. Start-up funding: "What was the source of capital used to start or initially acquire this business?"
    - Start-up funding from VC: equals 1 if answer is "Investment by venture capitalists," 0 otherwise
    - Start-up funding from banks: equals 1 if answer is "Business loan from a bank or financial institution." 0 otherwise
    - Start-up funding from family or friends: equals 1 if answer is "Business loan/investment from family/friend(s)," 0 otherwise
2. Current funding:

- Current funding from investors: equals 1 if answer to "What was the total amount of money this business received from angel investors, venture capitalists, or other businesses in return for a share of ownership in this business?" is positive, 0 otherwise
- Current funding from banks: equals 1 if answer to "What was the total amount of money this business borrowed from a bank or other financial institutions, including business loans, a business credit card carrying a balance, or a business line of credit?" is positive, 0 otherwise
- Current funding from grants: equals 1 if answer to "what was the total amount of money this business received from government grants (such as the Small Business Innovation Research (SBIR) and/or Small Business Technology Transfer (STTR) programs)?" is positive, 0 otherwise
- Current funding from family/friends: equals 1 if answer to "What was the amount of money this business received from family, friends, and employees?" is positive, 0 otherwise
- Current funding from owner: equals 1 if answer to "What was the total amount of money that the owner(s) personally put into the business?" is positive, 0 otherwise

3. Ownership:

   - Family-owned: equals 1 if answer to "Did two or more members of one family own the majority of this business?" is "Yes," 0 otherwise, where family members are defined as spouses, parents/guardians, children, siblings, or close relatives.

4. Innovation:

   - Patent, copyright, or trademark: equals 1 if answer to "Did this business own one or more of the following?" includes "Patent (granted)," "Patent (pending)," "Copyright," or "Trademark," 0 otherwise

A.I.5 Management and Organizational Practices Survey (MOPS)

The MOPS is a supplement to the Annual Survey of Manufactures and collects information on management practices of manufacturing establishments, which I study as firm outcomes when considering mechanisms.[95]

This dataset is an establishment-level survey of manufacturing firms, drawn from the Annual Survey of Manufactures survey panel.[96] The MOPS is collected every five years, beginning with coverage of management practices in 2010. I use this 2010 sample to study firms' management practices as outcomes; I aggregate from establishment-level to firm-level[97] by taking employment-weighted averages across establishments.[98]

The survey's questions aim to measure the structure of an establishment's management practices. This structure includes how businesses monitor production, set output targets, and incentivize workers. Bloom et al. (2019) argue that establishments with more robust management practices (e.g., having performance-, rather than tenure-, based pay) also tend to be more productive.

I construct several outcomes on management practices, analogous to those in the ASE above. The 2010 MOPS includes 16 questions on management practices, again divided into questions on monitoring and targeting production and questions on incentivizing workers. I follow Bloom et al. (2019) and normalize each question between 0 and 1,[99] where zero corresponds to the least structured practices (i.e., practices that are less explicit, formal, frequent, or specific) and one corresponds to the most structure practices, before aggregating by taking averages. For the original worksheet, see `https://www2.census.gov/programs-surveys/mops/technical-documentation/questionnaires/ma-10002_15_final_3-2-16.pdf`. These questions (with some abbreviations), and the normalizations, are presented below in Tables A.2 and A.3.

[95] The MOPS management questions are based on those in the World Management Survey (Bloom and Van Reenen (2007)), which is also the basis for the management survey conducted by Guiso, Pistaferri, and Schivardi (2020).

[96] For details, see `https://www.census.gov/programs-surveys/mops/about.html`.

[97] By firm-level, I mean the FIRMID-level.

[98] I aggregate across establishments, regardless of whether they are located in the set of states for which I have LEHD data; I do this to maximize precision in the average management practice scores, since establishment-level values tend to be very noisy.

[99] These normalizations are provided in the final version of the MOPS data.

Table A.2: 2010 MOPS management questions: Monitoring and targeting production

Question text	Answer text	Value
What best describes what happened at your firm when a service or production problem arose?	No action was taken	0
	We fixed it but did not take further action	1/3
	We fixed it and took action to make sure that it did not happen again	2/3
	We fixed it and took action to make sure that it did not happen again, and had a continuous improvement process to anticipate problems like these in advance	1
How many key performance indicators were monitored at your firm?	No key performance indicators	0
	1-2 key performance indicators	1/3
	3-9 key performance indicators	2/3
	10 or more key performance indicators	1
How frequently were the key performance indicators reviewed by managers at your firm?	Never	0
	Yearly	1/6
	Quarterly	1/3
	Monthly	1/2
	Weekly	2/3
	Daily	5/6
	Hourly	1
How frequently were the key performance indicators reviewed by managers at your firm?	See previous question	
Where are display boards showing service quality, output and other key performance indicators located in your firm?	We did not have any display boards	0
	All display boards were located in one place	1/2
	Display boards were located in multiple places	1
What best describes the time frame of operational targets at your firm?	No targets	0
	Main focus was on short-term (less than one year) targets	1/3
	Main focus was on long-term (more than one year) targets	2/3
	Combination of short-term and long-term targets	1
How easy or difficult would it have been to achieve business, service, or production targets at this business?	Minimal effort	0
	Extraordinary effort	1/4
	Less than normal effort	1/2
	Normal effort	3/4
	More than normal effort	1
Who was aware of the operational targets at your firm?	Only senior managers	0
	Most managers and some workers	1/3
	Most managers and most workers	2/3
	All managers and most workers	1

Table A.3: 2010 MOPS management questions: Incentives

Question text	Answer text	Value
What are non-managers' performance bonuses usually based on in your firm?	No performance bonuses	0
	Their entire company's performance	1/4
	Their local establishment or branch's performance	1/2
	Their team or shift performance	3/4
	Their own performance	1
When targets are met, what percent of non-managers received performance bonuses?	Targets not met	0
	0%	1/5
	1-33%	2/5
	34-66%	3/5
	67-99%	4/5
	100%	1
What are managers' performance bonuses usually based on in your firm?	See question for non-managers above	
When targets are met, what percent of managers received performance bonuses?	See question for non-managers above	
What was the primary way non-managers were promoted at this business?	Non-managers are not normally promoted	0
	Promotions were based mainly on factors other than performance and ability	1/3
	Promotions were based partly on performance and ability and partly on other factors	2/3
	Promotions were based solely on performance and ability	1
What was the primary way managers were promoted at this business?	See question for non-managers above	
When was an under-performing non-manager reassigned or dismissed?	Under-performing non-manager are not normally reassigned or dismissed	0
	After 6 months of identifying non-manager under-performance	1/2
	Within 6 months of identifying non-manager under-performance	1
When was an under-performing manager reassigned or dismissed?	See question for non-managers above	

A.I.6 Compustat-SSEL Bridge (CSB)

The CSB identifies publicly-traded firms by linking firms in the Census data to Standard & Poor's Compustat database, by year (Tello-Trillo and Streiff (2020)). I use this information to investigate whether exposure to more entrepreneurial coworkers predicts future entrepreneurs' firms becoming publicly traded.

A.I.7 Business Register (BR)

The BR provides information on the legal form of businesses, namely whether they are structured as corporations, sole proprietorships, partnership, or other forms. I use this information to conduct heterogeneity by legal type, in part to help interpret my measure of entrepreneurship.

The BR is a comprehensive database of U.S. business establishments that consolidates information from various Census Bureau and Federal data sources.[100] For each establishment, in each year, the BR indicates the legal form. I aggregate this information to the firm-level, creating indicators for whether each firm (FIRMID) is ever a (S- or C-) corporation, sole proprietorship, partnership, or other from 1994 through 2013. The vast majority of firms are only ever coded as one type.

[100]For details, see https://www.census.gov/econ/overview/mu0600.html.

I use this information to explore entrepreneurial spillovers within the different legal forms, asking, e.g., whether exposure to former entrepreneurs of corporations predicts that an individual will become an entrepreneur at a corporation, etc. This exercise is both itself interesting, since it is conceivable that former entrepreneurs may encourage their coworkers towards entrepreneurship of the same legal form, and helpful as a check on my definition of entrepreneurship.

A.I.8 Samples

I use several samples throughout this paper. I use data from 1994 to 2013 to describe aggregate patterns and to estimate my model. For the reduced form analyses, my primary sample contains individuals with coworkers in 2004 for whom I can measure previous and future entrepreneurial outcomes. For my analysis of outcomes from the ASE and MOPS, which are measured after 2010, I focus on later samples.

Model sample I use the initial sample of 1994 through 2013 to describe aggregate patterns in entrepreneurship and other economic outcomes and to estimate my model. In my reduced form analyses I focus on subsets of this initial sample.

Main reduced form samples For the bulk of the reduced form analysis, I focus on individuals and their coworkers in 2004; this timing allows me to study both prior and subsequent entrepreneurship of individuals and their coworkers.

Specifically, this sample allows me to identify whether a given individual was previously an entrepreneur within the past 5 (or more) years (1999-2003), is currently an entrepreneur (2004), and/or if they will become an entrepreneur within the next 5 years (2005-2009). This timing allows me to measure young firm characteristics for all entrepreneurs whose firms enter in 2005-2009; for a firm that enters in 2009, I can track its employment, etc., from 2009 through 2013.[101]

I restrict to individuals at establishments with at least two employees, i.e., individuals with coworkers. I also restrict to individuals aged 20-64 in the central year (e.g., 2004), but consider their coworkers aged 20-69 in that year. I make the restriction so that I can identify subsequent entrepreneurship in the next 5 years, i.e., when those individuals are between age 21 (2004 20 year-olds in 2005) and 69 (2004 64 year-olds in 2009).

In the intensive margin (i.e., firm characteristics) analyses, I further restrict to individuals who become entrepreneurs in the relevant years (e.g., 2005-2009 for the 2004 sample).

Survey samples When I study outcomes in the 2014-2016 ASE and 2010 MOPS surveys, I consider individuals and their coworkers in more years in order to increase statistical power, but otherwise follow the sample restrictions from the main reduced form samples. I consider two sets of samples.

First, I start with a broad sample of individuals who become entrepreneurs and whose entrepreneurial firms appear in either the ASE or MOPS (and for whom I can observe coworkers' recent entrepreneurship experience). For the ASE, I focus on individuals working between 1999 and 2012 and who become entrepreneurs within five years (or by 2013, for the later years).[102] I also use a subset of this ASE sample to analyze owner-specific values, as described in Section III.3, in which I match individuals to owners based on demographics. For the MOPS, I focus on individuals working between 1999 and 2009 and who become entrepreneurs within five years (or by 2010, for the later years). For both samples, I restrict to the last appearance (and set of coworkers) of each individual before they become an entrepreneur, in order to avoid double counting individuals.[103]

Second, I consider a more restricted, younger set of entrepreneurial firms, in order to reduce selection into the datasets driven by selection into survival. For the ASE outcomes, I match individuals in 2008-2012 who become entrepreneurs in 2013 to the ASE survey samples and restrict to the last appearance of each individual in the 2008-2012 window. For the MOPS outcomes, I match individuals in 2005-2009 who

[101]Note that the average characteristics of these entrepreneurs' firms that enter between 2005 and 2009 will be shaped by the Great Recession, but the regression estimates will be comparing firms within this group. Also, despite the Great Recession affecting entrepreneurship in the later years, exposure to more entrepreneurial coworkers in 2004 still predicts entrepreneurship in 2008 and 2009, as shown in Table A.15. I also show that my intensive margin results are robust to the inclusion of entry year fixed effects, as shown in Table A.11.

[102]I start with 1999 so that I can observe coworkers' 1994-1998 entrepreneurship experience. While the ASE begins in 2014, the last year I observe in the LEHD is 2012, such that the last possible entry year for entrepreneurs is 2013.

[103]An individual may appear multiple times in these samples if they become an entrepreneur to multiple firms that are surveyed.

become entrepreneurs in 2010 to the 2010 MOPS and restrict to the last appearance of each individual in the 2005-2009 window.

A.II Alternative hypotheses: Spawning, exposure to leaders, and workplace culture

While I argue that the positive extensive margin results are consistent with a story of entrepreneurial coworkers passing on entrepreneurial knowledge or skills (or generally inspiring) potential entrepreneurs, it is worth considering alternative hypotheses. Here I present evidence against interpreting the results as being the driven by entrepreneurial spawning (in which firms' behavior encourage entrepreneurship or entrepreneurial coworkers take individuals along on their next venture), exposure to firm leaders in general, and entrepreneurial coworkers only inducing individuals to leave the firm, for instance through creating unpleasant workplaces.[104]

Spawning Entrepreneurial spillovers do not appear to be driven by firm behavior promoting entrepreneurship nor by entrepreneurial coworkers bringing individuals along for their next entrepreneurial venture, collectively known as entrepreneurial spawning (also known as spin-outs or spin-offs) (Gompers, Lerner, and Scharfstein (2005)).

In the first version of spawning, it is possible that the spillovers I observe are driven by individuals leaving firms for entrepreneurship at particular stages in firms' careers. For instance, Babina, Ouimet, and Zarutskie (2018) find evidence that individuals become entrepreneurs after their employer has a successful initial public offering (IPO), arguing that these individuals receive wealth shocks from the IPO that allows them to depart to entrepreneurship. If firms that IPO, e.g., also attract former entrepreneurs as employees, then the spillovers that I measure could reflect entrepreneurial spawning from particular types of firms.

However, recall that spillovers are concentrated within establishments (Table 4), suggesting that the results are not wholly driven by firm shocks. Further, the results are not driven by individuals whose employers are at particular stages in the firm life cycle. That is, as shown in column 2 of Table A.7 when I control for firm age fixed effects, the coefficient on the share of coworkers with entrepreneurial coworkers is marginally decreased but still large. Similarly, when I interact the exposure with firm age (Figure A.3), I find spillovers at firms of all ages. Additionally, the extensive margin spillovers are robust to controlling for individuals' firms' revenue or revenue productivity, as shown in columns 6 and 7 in Table A.7, suggesting that the patterns are not driven by firm productivity. Finally, as Section III.6 below notes, spillovers exist in most sectors, with large spillovers in the accommodation and food service sector in which firms are unlikely to spawn entrepreneurs (since they rarely IPO, etc.). I conclude that the entrepreneurial spillovers I measure across coworkers is distinct from entrepreneurial spawning driven directly by firm behavior.

In the second version of spawning, it is possible that coworkers with entrepreneurial experience may not simply transmit information to potential entrepreneurs, but may also bring individuals along for their next entrepreneurial venture. In this case, these spillovers may not reflect "extra" firms, but rather just "extra" entrepreneurs. I investigate this possibility by exploring whether future entrepreneurs who are exposed to entrepreneurial coworkers are more likely to start firms with these coworkers.

In fact, individuals who work with more entrepreneurial coworkers are actually marginally more likely to start firms of which they are the only initial employee, as shown in column 1 of Table A.16. Relatedly, individuals exposed to more entrepreneurial coworkers are, on average, no more likely to start a new firm with any of their 2004 establishment coworkers, as shown in column 2 of Table A.16, in large part because many of these individuals are the only initial employee of their entrepreneurial firm. While spin-outs are present empirically — 24% of future entrepreneurs have a 2004 coworker as co-entrepreneur — they do not appear to drive the extensive margin result.

Exposure to leaders Entrepreneurial spillovers are also not driven by exposure to firm leaders in general, who may teach individuals leadership skills or human capital. Exposure to coworkers who were recently leaders of new firms, rather than firms of any age, disproportionately predict entrepreneurship.

I investigate the role of firm leaders in general by horse-racing spillovers from entrepreneurial coworkers and coworkers who were recently top earners at any firm, not just new ones. I estimate a version of model

[104] An additional alternative hypothesis that is difficult to test with administrative data is that entrepreneurial coworkers affect individuals' perceptions of or aversion to the riskiness of entrepreneurship, as Nanda and Sørensen (2010) note. I am unable to test this hypothesis with my data and consequently interpret any changes in perceived risk as changes to the cost of entrepreneurship, where that cost includes the psychic cost of the uncertainty of entrepreneurship.

(4) in which I add the share of coworkers who were recently (between 1999 and 2003) a top three earner at any firm. While exposure to top earners in general also predicts entrepreneurship, there is a distinct role for entrepreneurial coworkers: as shown in column 4 of Table A.16, the coefficient on the share of coworkers who were recently entrepreneurs in nearly three times larger than the coefficient on the share of coworkers who were recently a top earner at any firm. I interpret these results as evidence that the process of entrepreneurship — i.e., of being a top earner at a new firm — is a meaningful experience, above and beyond that of being a leader at a firm in general, from which others can learn.

Workplace culture Entrepreneurial spillovers are not driven simply by exposed individuals being more likely to leave their firm, for instance because their entrepreneurial coworkers create unpleasant workplace cultures.

If any individual changing jobs has some probability of becoming an entrepreneur, it is possible that the positive extensive margin result reflect entrepreneurial coworkers prompting individuals to simply leave their jobs, rather than actually prompting them to entrepreneurship specifically. For example, perhaps entrepreneurial coworkers encourage individuals to follow their career goals more generally, which might lead to job moves; or, perhaps entrepreneurial coworkers are "head-in-the-clouds" workers or generally frustrating peers, creating unhappy workplaces.

I investigate this alternative hypotheses by estimating model (4) for the subsample of individuals for whom their last year at the firm is 2004. For these individuals who leave the firm, I still find evidence of positive spillovers, as shown in column 5 of Table A.16. Amongst leavers, a one standard deviation (9.4 percentage point) increase in the share of coworkers who were recently entrepreneurs predicts a 0.37 percentage point increase in the likelihood of entrepreneurship, 9.1% of the mean outcome. I take this as evidence that the spillovers do not simply reflect individuals being pushed out of their jobs by their entrepreneurial coworkers.[105]

A.III Additional extensive margin heterogeneity and intensive margin outcomes

Here I present additional heterogeneity and outcome analyses.

A.III.1 Extensive margin heterogeneity

As Table 1 shows, individuals who become entrepreneurs tend to earn more than and are more likely to have graduated from college than individuals who do not become entrepreneurs, and so it is possible that higher earning and skilled individuals drive the estimated spillovers.[106]

In fact, in my context there is not substantial heterogeneity by earnings. I estimate model (4) but interact the exposure variable with dummies capturing in which quartile of the aggregate earnings distribution individuals' 2004 earnings fall. As shown in Table A.17, I find similar coefficients for all quartiles except for the lowest.[107] That is, individuals earning in the top 75 percent of the aggregate earnings distribution are similarly affected by spillovers, at least when compared coarsely in terms of earnings quartiles.

The fact that the bottom quartile experiences a much lower level of spillovers is not surprising for three reasons. First, some individuals in the bottom quartile are likely to not have the capital needed to start firms, and thus may not be able to take advantage of entrepreneurial opportunities. Second, some individuals in the bottom quartile are starting and/or leaving jobs in 2004; these individuals may consequently have less exposure to their 2004 coworkers, and thus may be less affected by those coworkers' entrepreneurial experiences. Third, some individuals in the bottom quartile are part-time workers, who may be uninterested in the time commitment of entrepreneurship.[108]

[105] This analysis is also evidence that the spillovers do not simply reflect entrepreneurial coworkers being clustered at firms that exit in 2004, for whom all individuals would be identified as leaving in 2004.

[106] Bernstein et al. (2018) argue that higher skill individuals are more responsive to entrepreneurial opportunities in the case of demand shocks.

[107] If instead I consider in which earnings quartile an individual's earnings falls *within their establishment*, I find the largest coefficient on the share of coworkers who were recently entrepreneurs for individuals the second highest quartile, although the pattern remains that all but the bottom quartile experiences relatively similar (and positive) spillovers. See column 2 of Table A.17 for these results.

[108] Note that for individuals switching jobs, I keep their highest paying firm (such that the data is at the individual-level) and only count their earnings at that firm. In an unreported analysis, I confirm that my main extensive margin estimates are robust to excluding the probable part-time workers, i.e., individuals earning below one quarter's worth of full-time minimum wage.

A.III.2 Intensive margin outcomes

Beyond the traditional measures of firm characteristics studied in Section IV, I explore other ways in which more exposed individuals entrepreneurial firms differ, which provide some intuition for mechanisms. I find that exposure to entrepreneurial coworkers does not predict a higher likelihood of becoming publicly traded by making an initial public offering (IPO). Furthermore, exposed individuals tend to start firms that are less innovative, generating fewer patents, copyrights, and trademarks. I find that, in some cases, entrepreneurs are more likely to start firms in the sectors in which their entrepreneurial coworkers ran firms. Finally, I find that these firms of more exposed individuals tend to have less within-firm earnings inequality, operate with less structured management practices, are more often financed by the owners, and are less likely to be family-owned.

Initial public offerings A standard measure of extreme success and desire to grow is whether a firm makes the transition to being publicly traded by making an initial public offering (IPO) (Brau and Fawcett (2006)). I investigate whether exposure to more entrepreneurial coworkers predicts whether an entrepreneur starts a firm that becomes publicly-traded (i.e., appears in the CSB). I estimate model (9) for outcomes of whether an entrepreneur's firm becomes publicly-traded within its first five years or ever between 2005 and 2016, the last year covered in the CSB data. Table A.18 presents the results: I find imprecise zeros for the coefficients on the share of coworkers who were recently entrepreneurs. Because becoming publicly-traded is a very rare event — only 0.1% of entrepreneurs start firms that ever become publicly-traded by 2016 — the estimates lack precision. However, the confidence intervals implied by the standard errors are still small and close to zero.[109] I conclude that entrepreneurs who are generally exposed to more entrepreneurial coworkers are not dramatically more or less likely to start firms that become publicly-traded.

Innovation Another measure of firm performance is innovation: historically, firms that innovate, as observed through patents, have higher market values and productivity (Bloom and Van Reenen (2002)). Because entrepreneurs who worked with more entrepreneurial coworkers tend to start less successful firms, on average, it is likely they also start less innovative firms. Nonetheless, these entrepreneurial coworkers could actually promote innovation without improving success as captured by my metrics; for example, they might direct innovative individuals towards entrepreneurship as the best avenue for them to develop and create their own products but not teach them the skills needed maintain their businesses.

I investigate the connection between exposure to entrepreneurial coworkers and innovation by using a broad sample of individuals in 1999-2012 who become entrepreneurs within five years and whose firms are covered by the 2014-2016 ASE; I restrict to the most recent (prior to the entrepreneurship) appearance in the LEHD in order to avoid double counting individuals. I estimate a version of model (9) for the outcome of whether an entrepreneur's firm reports that it owns any patents (pending or granted), copyrights, or trademarks. As column 10 of Table A.19 shows, entrepreneurs who worked with more entrepreneurial coworkers are less likely to start firms that report owning patents, copyrights, or trademarks. A one standard deviation (15.9 percentage point) increase in the share of entrepreneurial coworkers predicts a 0.4 percentage point lower likelihood, a 2% decrease relative to the mean.

Sector choice Beyond impacting an individual's likelihood of becoming an entrepreneur and their ultimate success, entrepreneurial coworkers may also affect the type of firm they start. In particular, entrepreneurial coworkers may push individuals towards (or away from) the sectors in which they were entrepreneurs, since the coworkers may have particular industry knowledge or networks that they can transmit to an individual. Because past industry experience is a strong predictor of entrepreneurial success (Azoulay et al. (2020)), it is plausible that exposure to entrepreneurs from a particular industry may serve as a substitute for personal experience in that sector.

I explore the role of exposure to entrepreneurial coworkers in determining which sector entrepreneurs enter by estimating versions of model (9) in which I predict whether future entrepreneurs start firms in each sector from their entrepreneurial coworkers conditional, as usual, on the industry in which they work in 2004. For each sector separately, I estimate two different versions of this model. First, I estimate the role of general exposure to entrepreneurial coworkers; this is informative about whether entrepreneurs who worked

[109] For example, the standard error for the estimated coefficient on the share in column 1 of Table A.18, 0.00023, indicates that I can reject the null hypotheses that a one standard deviation increase in the share of entrepreneurial coworkers predicts a greater (in magnitude) than 0.011 percentage point (10.5% of the mean outcome) lower or greater than 0.003 percentage point (2.6% of the mean outcome) higher likelihood of becoming publicly traded within 5 years.

with more entrepreneurial coworkers tend to enter particular sectors. Second, I add to the model the share of entrepreneurial coworkers whose past entrepreneurial firms' belonged to the given sector, conditional on that sector being different from the individual's 2004 establishment's sector.[110] This version speaks to the hypothesis that these entrepreneurial coworkers can transmit new industry knowledge to the individual; for instance, if an individual working in construction has a coworker who ran a restaurant, they may learn new knowledge about the restaurant industry that prompts them to subsequently start a restaurant themself.

As Table A.20 shows, the estimates for these models vary substantially across sectors. In the odd columns, I find that general exposure to entrepreneurial coworkers predicts that entrepreneurs start firms in agriculture, wholesale trade, finance and insurance, management, and arts and entertainment and not in manufacturing, administrative services, health, and accommodation and food services.[111] While the coefficients are relatively small, in proportion to the sector entry rates, they are meaningful: for instance, a one standard deviation (14.7 percentage point) increase in the share of coworkers who were recently entrepreneurs predicts that an entrepreneur is 0.09 percentage points more likely to start a firm in wholesale trade, a 1.7% increase relative to the mean. It also worth noting that these estimates account for individuals' 2004 establishments' industry (through the inclusion of 6-digit industry fixed effects); 45.3% of these entrepreneurs start firms in the same sector as their 2004 establishment, so relatively small shifts in entrepreneurial sector choice are still meaningful.

When I include exposure to entrepreneurial coworkers from sectors other than the 2004 establishment's sector in the models, I find striking results. As shown in the even columns of Table A.20, there is substantial heterogeneity across sectors, with some of these "outsider" entrepreneurial coworkers seemingly pushing entrepreneurs away from their past entrepreneurial sectors, while others predict that entrepreneurs enter their past sector. In particular, entrepreneurs are more likely to start firms in construction, professional, scientific and technical services, and accommodation and food services if they worked in another sector in 2004 with coworkers who had entrepreneurial experience in those sectors. These findings suggest that these entrepreneurial coworkers may be providing sector-specific knowledge or help to individuals and are consistent with survey evidence by Bosma et al. (2012), who find that entrepreneurs' role models tend to operate in the same sector as them. A further investigation as to why the patterns vary by entrepreneurial sector may provide more insight into precise mechanisms.

Average pay and inequality Since hiring employees is an important component of running a firm, former entrepreneurs may provide guidance on how to hire high-quality employees and how to pay them. Young firms in general tend to have lower average pay and lower within-firm earnings inequality than older firms (Sorkin and Wallskog (2021)), but entrepreneurial spillovers may generate variation in these patterns. Relatedly, more productive firms tend to have higher pay on average and across the within-firm pay distribution, but higher within-firm pay inequality (Bloom et al. (2021)). Since the entrepreneurial spillovers predict marginally higher productivity on average, especially if individuals work with more productive entrepreneurial coworkers (Table 9), it is plausible that entrepreneurial spillovers predict higher pay and inequality.

I explore spillovers to pay and inequality by estimating versions of model (9), where I in turn consider as outcomes entry year average earnings and within-firm earnings inequality.[112] These outcomes are informative both about the quality and diversity of the workforce at firms and about how attractive a firm may be to potential employees. Table A.21 presents the estimates; future entrepreneurs who worked with more entrepreneurial coworkers tend to start firms with higher mean log earnings and lower pay inequality (measured both as variance of log earnings and the 90-10 gap of log earnings). These results suggest that entrepreneurial spillovers may generate firms that are more attractive to workers.

However, because these firms are also smaller (Table 9), these "benefits" may be limited. Indeed, when I include as a covariate the size of the future entrepreneurs' firms upon entry, the coefficients on the share of coworkers with recent entrepreneurship are significantly dampened, if not effectively zeroed, as shown in

[110] Specifically, this variable is the share of coworkers who were entrepreneurs and whose entrepreneurial firms were in the outcome sector; if the individual's 2004 establishment is in the outcome sector, this variable is replaced by 0.

[111] Recall that these models are comparing individuals who become entrepreneurs between 2005 and 2009 (and who I observe in 2004) who have different exposure to entrepreneurial coworkers in 2004; this means that these results do not just reflect which sectors have more entrepreneurship between 2005 and 2009, since I am comparing entrepreneurs within that time period.

[112] Note that the mean values of inequality here are substantially larger than in other papers, including in Sorkin and Wallskog (2021), because they include part-time workers and workers who move firms.

the even columns of Table A.21. These results suggest that exposure to entrepreneurial coworkers does not result in dramatically different pay policies or worker quality, on average, when comparing entrepreneurial firms of the same size.

Management structure Guiso, Pistaferri, and Schivardi (2020) argue that learning management skills may be one important way in which entrepreneurship leads to more entrepreneurship. The 2015 ASE and 2010 MOPS both collect information on how structured firms' management protocols are, and I can use these surveys to analyze this question.

I focus on the 2015 ASE, since it covers firms across the economy, while the MOPS is restricted to manufacturing firms.[113] I study a broad sample of individuals who appear and have coworkers in the LEHD between 1999 and 2012 and who become entrepreneurs within 5 years (or by 2013, the end of the data); for each instance of entrepreneurship, I restrict to the most recent (prior to the entrepreneurship) appearance in the LEHD in order to avoid double counting individuals.

For the sample of individuals who become entrepreneurs to firms that appear in the 2015 ASE, I study whether these entrepreneurs' firms have different management styles based on their past exposure to entrepreneurial coworkers. I estimate versions of model (9) for three measure of management style: an overall management structure score that captures how structured a firm's management is, as well as two sub-scores that capture how structured the monitoring and targeting practices are and how performance-oriented promotions, bonuses, and reassignments/dismissals are, respectively. All three of these scores are based on several questions and are normalized to take values between 0 and 1.[114] Because firms' management styles may evolve over their life cycles and may depend on when firms enter the economy, I additionally control for year (in which I observe the coworkers)-by-entrepreneurial firm entry year fixed effects.

The results are striking and inconsistent with Guiso, Pistaferri, and Schivardi (2020): as shown in column 1 of Table A.23, entrepreneurs who previously worked with more entrepreneurial coworkers tend to run firms with less structured management practices, and this is true if I compare entrepreneurial firms within the same industry (i.e., by adding fixed effects in column 2).[115] These results persist if I consider the management subscores separately — more exposed entrepreneurs' firms are less structured both in terms of how they monitor and target production and how they incentivize workers.

It is possible that these results are biased by survival differences: as shown in previously in this section, entrepreneurs who work with more entrepreneurial coworkers tend to start firms that survive for fewer years, such that the analysis here might be impacted by differential selection into surviving to the point of being surveyed by the 2015 ASE. While the inclusion of year-by-entrepreneurial firm entry year fixed effects should control for some of these differences — i.e., the regressions are not directly comparing individuals who started firms in 2000 to those who started firms in 2013 — I conduct robustness by studying a restricted sample. I restrict to individuals who appear in the LEHD between 2008 and 2012 and who become entrepreneurs in 2013; as columns 3, 6, and 9 in Table A.23 show, this sample restriction leads to decreases in precision but coefficients that are generally consistent with those from the broader sample.

These results, while surprising in light of the findings in Guiso, Pistaferri, and Schivardi (2020), are not surprising in the scope of the rest of the intensive margin results of this paper. On average, the individuals who become entrepreneurs after working with more entrepreneurial coworkers tend to start less successful firms, and so it is consistent that they also are not structured managers.[116] These results suggest that the average individual who becomes an entrepreneur after working with entrepreneurial coworkers likely did not

[113] In the appendix, I also provide results for the small number of entrepreneurs whose entrepreneurial firms are surveyed by the 2010 MOPS. For this sample, I find modestly positive but quite noisy coefficients, as shown in Table A.22. For example, in column 1, a one standard deviation (11.3 percentage points) increase in the share of entrepreneurial coworkers predicts a 0.005 higher overall management score, a 0.8% increase relative to the mean. My current hypothesis for why the patterns differ between the MOPS and the ASE is that the patterns may be different for manufacturing firms; future research should investigate how managerial behavior may be different across sectors.

[114] See the online appendix of Bloom et al. (2019) and Section A.I of this paper for the details of the MOPS and ASE, including a complete list of the questions. The overall management score is the average of all 16 questions in the MOPS; the monitoring and targeting score is the average of the first 8, and the incentives score is the average of the last 8. I map the ASE questions to the MOPS ones.

[115] Note that the magnitudes are modest. A one standard deviation (15.1 percentage point) increase in the share of coworkers who were recently entrepreneurs predicts a 0.004 lower overall management score, a 0.7% decrease relative to the mean score.

[116] Bloom et al. (2019) argue that manufacturing firms with higher management scores are also more productive firms, so the fact that, e.g., firm survival and management are similarly affected by entrepreneurial exposure is unsurprising.

gain substantial managerial skills from those coworkers.[117]

Financing For individuals considering entrepreneurship, one potential stumbling block is financing. Entrepreneurial coworkers may also help prospective entrepreneurs with financing, either directly investing in their firms or connecting them with outside investors or banks. I investigate this possibility by studying reported sources of start-up and general financing for firms in the ASE.

For the broad sample of individuals in 1999-2012 who become entrepreneurs within five years and whose firms are covered by the ASE used to study management above, I estimate versions of model (9) with outcomes on whether the entrepreneurial firms had start-up funding from venture capitalists (VC), banks, and/or family or friends as well and current funding from outside investors (including VC), banks, government grants, family or friends, and the owner themself. Table A.19 presents the results.

While the analyses lack precision because of the relatively small sample size, entrepreneurs who worked with more entrepreneurial coworkers do not appear to be more likely to have start-up or current funding from outside investors, banks, and family or friends. If anything, these more exposed entrepreneurs are more likely to fund their firms themselves — in column 8, the statistically significant coefficient on the share of entrepreneurial coworkers suggests that a one standard deviation (15.1 percentage point) increase in the share of coworkers who were entrepreneurs predicts that an entrepreneur's firm is 0.5 percentage points more likely to report that the owner currently personally puts money into the business, a 0.7% increase relative to the mean. This increase is modest, but alongside the other financing results is consistent with a story of entrepreneurial coworkers encouraging entrepreneurship without providing direct help, either through their own investment or through their finance networks.

Hereditary entrepreneurship and family ownership While I argue that entrepreneurial spillovers from coworkers can be important forces behind an individual's decision to become an entrepreneur, there are many other reasons individuals may pursue entrepreneurship. One widely cited reason is parental entrepreneurship: individuals whose parents have entrepreneurial experience are disproportionately likely to become entrepreneurs (Hvide and Oyer (2018), Akcigit et al. (2021)). For individuals with entrepreneurial parents, the impact of transitory coworkers likely pales in comparison to the lessons and capital input from their parents. Indeed, Nanda and Sørensen (2010) argue that entrepreneurial coworkers do not push individuals who have entrepreneurial parents towards entrepreneurship.

While I do not have access to parental entrepreneurship information,[118] I investigate whether individuals who work with more entrepreneurial coworkers are more or less likely to start family-owned firms (in which two or more members of the same family own the majority of the firm). If having entrepreneurial coworkers is a substitute for having entrepreneurial parents, and entrepreneurial parents contribute capital to their children's firms, I expect entrepreneurs who worked with more entrepreneurial coworkers to start firms that are not family-owned.

I investigate this using the broad sample of individuals in 1999-2012 who become entrepreneurs within five years and whose firms are covered by the ASE used above. I estimate a version model (9) for the outcome of whether an entrepreneurs' firm reports that it is family-owned in the ASE (i.e., whether two or more members of one family own the majority of the firm). As column 9 of Table A.19 shows, more exposed entrepreneurs indeed are less likely to start family-owned firms, although the relationship is relatively small: a one standard deviation (15.1 percentage point) increase in the share of coworkers with entrepreneurial coworkers predicts that an entrepreneur's firm is 0.8 percentage points less likely be family-owned, a 2.1% decrease relative to the mean. This result is consistent with the idea that having entrepreneurial coworkers provides a different pathway to entrepreneurship than having entrepreneurial parents.

[117]One possible reason for the discrepancy between my findings and those in Guiso, Pistaferri, and Schivardi (2020) is the context: Guiso, Pistaferri, and Schivardi (2020) study exposure to active firms, which are likely more successful and possibly more structured in their management styles than the entrepreneurial coworkers in my setting.

[118]It is, in theory, possible to link children to parents and analyze hereditary entrepreneurship using the LEHD. (Staiger (2020) links parents to children in the LEHD to study intergenerational employment patterns.) However, because of the short window in which I measure entrepreneurship, it would be difficult to measure entrepreneurship of both parents and children. I leave this avenue for future research

A.IV Reconciling with Lerner and Malmendier (2013)

In the literature on entrepreneurial spillovers across individuals, Lerner and Malmendier (2013) offer some of the best-identified evidence on spillovers, leveraging random assignment of Harvard MBAs students to class sections (and thus peers). Yet, their findings are strikingly different from my main results: Lerner and Malmendier (2013) find that class sections with more students with entrepreneurial experience actually general fewer subsequent entrepreneurs, which they argue is driven by a decline in unsuccessful entrepreneurship. The authors interpret these patterns as evidence of former entrepreneurs dissuading ventures that are unlikely to succeed. Meanwhile, I find positive extensive margin spillovers, suggesting, at least on net, no evidence of dissuasion. How can we reconcile these findings?

I argue that context matters. While random assignment of Harvard MBA students to class sections makes the findings of Lerner and Malmendier (2013) internally valid, the former and potential entrepreneurs among these classes are unlikely to represent the general population of entrepreneurs.[119] Harvard MBA students are likely wealthier, more educated, and younger than the average entrepreneur in the U.S., and likely start firms in different sectors.[120]

In an attempt to reconcile my findings with Lerner and Malmendier (2013), I seek a group of entrepreneurial coworkers who are comparable to Harvard MBA students. I do this in two ways. First, I simply use one of my measures that identifies particularly successful entrepreneurs, i.e., entrepreneurs whose firms were in the top 10% of entry year log employment; since Harvard MBAs are likely relatively successful as entrepreneurs, entrepreneurs who start large firms in my data may be a similar group. Second, I seek a group similar to the Harvard MBAs in a way unrelated to entrepreneurial success. While the LEHD demographics data does contain information on education, it is only available for a small fraction of individuals and is very coarse, with the highest level of education recorded being college; this makes using education as a proxy for like-MBA status impractical. Instead, I focus on earnings and investigate whether individuals experience entrepreneurial spillovers from their entrepreneurial coworkers who earn above $100,000 (in 2010 USD).[121]

I investigate whether these "like-Harvard MBA" entrepreneurs dissuade their coworkers from become entrepreneurs by estimating versions of model (8). As columns 2 and 3 of Table A.24 show, exposure to these types of entrepreneurial coworkers marginally push individuals towards entrepreneurship (i.e., the coefficients on the shares are positive), such that there is no evidence that these groups on net dissuade entrepreneurship.

Yet, it is possible that these "like-Harvard MBA" entrepreneurial coworkers dissuade ventures that are unlikely to succeed, as Lerner and Malmendier (2013) argue. To investigate this, I estimate modified versions of model (8) in which I integrate into the outcome variable a measure of firm success, similar to how Lerner and Malmendier (2013) study future entrepreneurial success. First, I study whether these "like-Harvard MBAs" encourage or prompt successful entrepreneurship. I estimate models in which the dependent variable is an indicator equal to 1 if an individual becomes an entrepreneur in the next five years *and* their entrepreneurial firm has entry year log employment in the top 10%, relative to firms that enter in the same year and industry, and 0 otherwise. The estimates of these regressions, shown in columns 4-6 of Table A.24, reflect the patterns previously documented in this section: individuals who are exposed to more entrepreneurs in general tend to be less likely to start firms that are particularly large, while those exposed to the "like-Harvard MBA" entrepreneurial coworkers are more likely to start firms that are particularly large.

Next, I study whether the "like-Harvard MBAs" dissuade unsuccessful entrepreneurship. I estimate models in which the dependent variable is an indicator equal to 1 if an individual becomes an entrepreneur in the next five years *and* their entrepreneurial firm has entry year log employment in the bottom 90%, relative to firms that enter in the same year and industry, and 0 otherwise. The estimates of these regressions,

[119] Furthermore, MBA programs are typically involve extensive networking, such that the types of interactions within MBA programs might be quite different from the interactions of coworkers at firms.

[120] Lerner and Malmendier (2013) do not provide a summary of the industries in which the former entrepreneurs ran firms, but they provide some examples, including businesses on college campuses, food service or retail companies, and software firms.

[121] In the 2005 Current Population Survey (CPS), 6.6% of individuals with positive 2004 income and wages report earning above $100,000 (in 2010 USD). Among individuals with at least a bachelor's degree, this share is, as expected, higher: 17.5%; among individuals with at least a master's degree, the share is again higher: 26.3%. I source CPS data from IPUMS (Flood et al. (2020)).

shown in columns 7-9 of Table A.24, show some evidence of dissuasion. Individuals who are exposed to more entrepreneurs in general are more likely to start unsuccessful firms, but this is partially offset if those entrepreneurial coworkers started particularly large firms or are high earners.

These patterns suggest that, as Lerner and Malmendier (2013) argue, there is some scope for former entrepreneurs dissuading future entrepreneurship, particularly less successful future entrepreneurship. However, these patterns are restricted to particular circumstances and may only be relevant for individuals who work with special coworkers. The vast majority of the population do not work with Harvard MBA-type coworkers, and so my findings may be more relevant in the broad context.

A.V Additional tables

This section presents additional empirical results, as described in the main text of the paper and in Sections A.II, A.III, and A.IV (in order of appearance in the text).

Table A.4: Exposure to any entrepreneurial coworkers predicts entrepreneurship, particularly at smaller establishments

Dependent Variable:	Entrepreneur 2005-2009
	(1)
Any coworkers with entrepreneurship $\times$ Emp $\in [0, 24]$	0.006***
	(0.000)
Any coworkers with entrepreneurship $\times$ Emp $\in [25, 99]$	0.005***
	(0.000)
Any coworkers with entrepreneurship $\times$ Emp $\in [100, \infty)$	0.003***
	(0.000)
Model (4) controls	x
$\mathbb{1}\{\text{Emp} \in [0, 24]\}$	x
$\mathbb{1}\{\text{Emp} \in [25, 99]\}$	x
Mean(dep var)	0.031
N	46,680,000

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that extensive margin spillovers are not driven by the linear-in-means functional for of model (4); rather, individuals who work with *any* entrepreneurial coworkers, particularly those at smaller establishments, are more likely to become entrepreneurs. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments. The table present estimates of (4) where I replace the variable on the share of coworkers with entrepreneur experience with variables on whether the individual has any entrepreneurial coworkers interacted with the establishment's size (only counting individuals for whom the establishment is their primary establishment), with controls indicated in the footer (including indicators for being in each establishment employment bin; model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). 21.4% of individuals are in establishments with 24 or fewer employees; 18.6% are in establishments with 25-99 employees; 60.0% are in establishments with 100+ employees. Standard errors are robust and clustered at the establishment level.

Table A.5: Extensive margin spillovers exist regardless of when coworkers joined firm

	Dependent Variable: Entrepreneur 2005-2009 (1)
Share of coworkers with entrepreneurship and joined before	0.036*** (0.001)
Share of coworkers with entrepreneurship and joined in same year	0.005*** (0.001)
Share of coworkers with entrepreneurship and joined after	0.074*** (0.002)
Model (4) controls	x
Share of coworkers who joined in each year, 1994-2004	x
N	46,680,000

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that the extensive margin spillovers exist regardless of when the entrepreneurial coworkers joined the firm, relative to the individual, including coworkers who joined after them (i.e., who the individual should not have selected on when joining). The table presents regression estimates of model (4), breaking out the share of coworkers who were recently entrepreneurs into three categories based on whether the coworkers joined before, in the same year, or after the individual, performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004, with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). Standard errors are robust and clustered at the establishment level. Mean of dep var is 0.034. Mean (std dev) of share entr. and ... joined before is 0.013 (0.061); joined in the same year is 0.014 (0.070); and joined after is 0.007 (0.024).

Table A.6: Having entrepreneurial coworkers is not a compensating differential for the average new hire

	Dependent Variable: Log 2004 Earnings (1)	(2)
Share of coworkers with entrepreneurship	0.084*** (0.024)	0.151*** (0.021)
Model (4) controls	x	x
Log 2003 total earnings		x
N	13,970,000	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence against the idea that individuals seek out and pay for the opportunity to work with entrepreneurial coworkers. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments who are new hires at their firm in 2004. The columns present estimates of several adaptations of model (4) with different controls, as indicated in the footer (here, model (4) controls are log establishment employment, own recent entrepreneurship, demographics, and age, industry, and state fixed effects measured at the time of exposure; i.e., excluding log earnings as a control), where I replace the dependent variable with the individual's log earnings at their firm in 2004. In column 2, I control for the individual's log total earnings in 2003, summing across all employers; if an individual does not have 2003 earnings, I replace this value by the mean and control for this using an indicator. Mean of the dependent variable is 9.756. Mean (std dev) of share of coworkers who were recently entrepreneurs is 0.035 (0.089).

Table A.7: Additional robustness to extensive margin spillovers

	Dependent Variable: Entrepreneur 2005-2009						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of coworkers with entrepreneurship	0.025***	0.022***	0.021***	0.024***	0.028***	0.025***	0.025***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log employment	x	x	x	x	x	x	x
Own entrepreneurship	x	x	x	x	x	x	x
Demographics	x	x	x	x	x	x	x
Log annual earnings	x	x	x	x	x	x	x
Age FE	x	x	x	x	x	x	x
Industry FE	x		x	x	x	x	x
State FE	x		x	x	x	x	x
Industry-State FE		x					
Firm age FE			x				
First year at firm FE				x			
Within-firm earnings bin FE					x		
$\mathbb{1}\{\text{Missing revenue}\}$						x	x
Firm log revenue						x	
Firm log revenue/employment							x
N				46,680,000			

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that the extensive margin spillovers are robust to the inclusion of several additional controls, including industry-by-state, firm age, tenure, and earnings bin fixed effects; past entrepreneurial exposure; and the firm's productivity. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments. The columns present estimates of several adaptations of model (4) with different controls, as indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). In the final two columns, firms with missing revenue information (i.e., does not have LBD revenue data) have revenue or productivity values replaced by the mean; this is controlled for with a missing indicator. Column 1 presents the main baseline results from Table 3 for comparison.

Table A.8: Additional robustness to extensive margin spillovers: Single-location establishments

	Dependent Variable: Entrepreneur 2005-2009		
	(1)	(2)	(3)
Share of coworkers with entrepreneurship	0.013*** (0.001)	0.013*** (0.001)	0.019*** (0.001)
Log employment	x	x	x
Own entrepreneurship	x	x	x
Demographics	x	x	x
Log annual earnings	x	x	x
Age FE	x	x	x
Industry FE	x	x	
State FE	x	x	x
ZIP code FE		x	
Zip code-Industry FE			x
N		20,200,000	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents additional evidence that the extensive margin results are robust to including finer geographic and geographic-by-industry fixed effects. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments that (a) are single-location establishments (i.e., the SEIN has one "SEIN-unit") and (b) are mappable to a physical establishment in the LBD from which I can identify the establishment's ZIP code. The columns present estimates of several adaptations of model (4) with different controls, as noted in the footer. Mean of the dependent variable is 0.044. Mean (std dev) of share of coworkers who were recently entrepreneurs is 0.055 (0.131).

Table A.9: Extensive margin spillovers exist, but are not only, from very recent entrepreneurs

	Dependent Variable: Entrepreneur 2005-2009									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share of coworkers with entrepreneurship	0.024***	0.024***	0.025***	0.025***	0.025***	0.026***	0.026***	0.026***	0.027***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Model (4) controls	x	x	x	x	x	x	x	x	x	x
Coworker entr. within past __ years	1	2	3	4	5	6	7	8	9	10
Mean(share)	0.008	0.015	0.022	0.028	0.034	0.039	0.045	0.051	0.056	0.060
Std dev(share)	0.054	0.071	0.081	0.089	0.095	0.100	0.105	0.108	0.111	0.114
N	46,680,000									

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that the extensive margin spillovers are similar regardless of how recent I measure coworkers' entrepreneurship. The table presents regression estimates of model (4) performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004 based on the share of coworkers who entrepreneurs within the past 1, ..., 10 years, with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). (Column 5 is the baseline estimate from Table 3.) Standard errors are robust and clustered at the establishment level.

Table A.10: Extensive margin spillovers depend on relative age and own entrepreneurial experience

	Dependent Variable: Entrepreneur 2005-2009 (1)
Panel A: Spillovers strongest from *relatively* older entrepreneurial coworkers	
Share of coworkers with entrepreneurship and younger	0.016***
	(0.001)
Share of coworkers with entrepreneurship and same age	0.020***
	(0.001)
Share of coworkers with entrepreneurship and older	0.033***
	(0.001)
Model (4) controls	x
Share coworkers younger	x
Share coworkers same age	x
Share coworkers older	x
N	46,680,000
Panel B: Spillovers lead to *new* entrepreneurs	
Share of coworkers with entrepreneurship	0.042***
	(0.001)
Previous entrepreneur	0.039***
	(0.000)
Share of coworkers with entrepreneurship × Previous entrepreneur	-0.049***
	(0.001)
Model (4) controls	x
N	46,680,000

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that extensive margin spillovers are strongest when coworkers are relatively older (Panel A) and when the individual has no recent entrepreneurial experience (Panel B). The table presents regression estimates of adapted versions of model (4) performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004, with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). Panel A replaces as the main explanatory variable the share of coworkers with recent entrepreneurship with three variables: the share of coworkers with entrepreneurial experience *and* who are younger than the individual, the share of coworkers with entrepreneurial experience *and* who are the same age as the individual, and the share of coworkers with entrepreneurial experience *and* who are older than the individual; the regressions also include controls for the share of all coworkers who are younger, the same age, and older than the individual. I bin an individual's coworkers into three bins based on the relative ages: those "younger" than the individual (i.e., between age 20 and their age minus 3, inclusively); those the "same age" as their (i.e., between their age minus 2 and their age plus 2, inclusively); and those "older" than their (i.e., between their age plus 3 and 69, inclusively). Panel B includes the interaction of the individual's own previous entrepreneurship with the share of their coworkers who were recently entrepreneurs. (Note that Panel B explicitly presents the coefficient on previous entrepreneurship, while that coefficient is suppressed in other tables.) Standard errors are robust and clustered at the establishment level. Mean (std dev) of: share of coworkers with entrepreneurship and younger = 0.020 (0.053); share of coworkers with entrepreneurship and same age = 0.005 (0.039); share of coworkers with entrepreneurship and older = 0.0164 (0.064).

Table A.11: Additional robustness to intensive margin spillovers

	Dependent Variable: 2005-2009 Entrepreneurial Firm Survives to Age 2									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share of coworkers with entrepreneurship	-0.010***	-0.039***	-0.009***	-0.033***	-0.010***	-0.039***	-0.009***	-0.032***	-0.038***	-0.039***
	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)	(0.002)	(0.011)	(0.011)	(0.011)
Share of coworkers with entr. and survived to age 2		0.031***		0.025**		0.032***		0.024**	0.030***	0.031***
		(0.011)		(0.011)		(0.011)		(0.011)	(0.011)	(0.011)
Model (4) controls	x	x	x	x	x	x	x	x	x	x
Entr. industry FE			x	x						
Entry year FE					x	x				
Entr. industry-Entry year FE							x	x		
$\mathbb{1}\{\text{Missing revenue}\}$									x	x
Firm log revenue									x	
Firm log revenue/employment										x
N	1,456,000									

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that the intensive margin spillovers (in particular, those measured in terms of firm survival) are robust to several specification extensions. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments who become entrepreneurs between 2005 and 2009. The columns present estimates of several adaptations of model (9) for the outcome of whether an individual's entrepreneurial firm survives to a second year, with different controls, as indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). "Entr. industry FE" indicates fixed effects for the future entrepreneur's firm's entry year 6-digit industry; "Entry year FE" indicate fixed effects for the future entrepreneur's firm's entry year. "Entr. instury-Entry year FE" indicate the entrepreneurs' industry-by-entry year fixed effects. In the final two columns, firms with missing revenue information (i.e., does not have LBD revenue data) have revenue or productivity values replaced by the mean; this is controlled for with a missing indicator. Columns 1 and 2 present the main baseline results from Table 8 for comparison. Standard errors are robust and clustered at the establishment level. Mean of dep var is 0.815. Mean (std dev) of share of coworkers with entrepreneurship is 0.064 (0.147); mean (std dev) of share of coworkers with entrepreneurship and whose entrepreneurial firm survived to age 2 is 0.057 (0.143).

Table A.12: Entrepreneurs who worked with more entrepreneurial coworkers have lower entrepreneurial wages

	Dependent Variable: Entry Year Log(Earnings) as Entrepreneur 2005-2009							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of coworkers with entrepreneurship	-0.164***	-0.162***	-0.163***	-0.160***	-0.184***	-0.180***	-0.183***	-0.178***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Share of coworkers with entr. and top 10% entry year log(employment)					0.357***	0.338***	0.355***	0.339***
					(0.026)	(0.026)	(0.026)	(0.026)
Model (4) controls	x	x	x	x	x	x	x	x
Entr. industry FE		x				x		
Entry year FE			x				x	
Entr. industry-Entry year FE				x				x
N	1,456,000							

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that future entrepreneurs' labor earnings as entrepreneurs depend on the relative success of their entrepreneurial coworkers' firms. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments who become entrepreneurs between 2005 and 2009. The columns present estimates of (9) for the wage and salary income that the entrepreneur earns at their entrepreneurial firm in its entry year, with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). "Entr. industry FE" indicate fixed effects for the future entrepreneur's firm's 6-digit industry (at entry); "Entry year FE" indicates fixed effects for the entry year, and "Entr. industry-Entry year FE" indicate industry-by-entry year fixed effects. The second reported variable ("top 10%") is the share of coworkers who were entrepreneurs and whose entrepreneurial firm's entry year log employment was in the top 10% of firms that entered in the same year and 6-digit industry. Standard errors are robust and clustered at the establishment level. Mean of dep var is 9.832. Mean (std dev) of share is 0.064 (0.147). Mean (std dev) of share top 10% is 0.009 (0.038).

Table A.13: Additional robustness to entrepreneurship measurement

	Dependent Variable: Entrepreneur 2005-2009						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of coworkers with entrepreneurship	0.025***	0.025***	0.021***	0.015***	0.023***	0.025***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Model (4) controls	x	x	x	x	x	x	x
Entrepreneurship definition	Main	LEHD Age	Top 1	Corporations	Sole proprietorships	Partnerships	Other Legal Form
Mean(dep var)	0.031	0.026	0.014	0.021	0.005	0.007	0.002
Mean(share)	0.034	0.029	0.014	0.024	0.006	0.005	0.006
Std Dev(share)	0.095	0.088	0.059	0.083	0.038	0.033	0.036
Number individuals				46,680,000			

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that the extensive margin spillovers are robust to varying the definition of entrepreneurship. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments. The columns present estimates of several adaptations of model (4) with different controls, as noted in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). Column 1 provides the baseline estimate from Table 3 for comparison. In column 2, I define entrepreneurship (for both the dependent and independent variables, including the unreported controls of own recent entrepreneurship) as being one of the top 3 annual earners at a firm at LEHD firm age 0 (based on an calculation of firm age provided by the Census). In column 3, I define entrepreneurship as being the top annual earner at a new firm, based on my definition of firm entry (based on entry to the LEHD and LBD). In columns 4-7, I define entrepreneurship as being one of the top 3 annual earners at a new firm of a given legal type; I identify firms' legal types from the Business Register (BR), and label a firm as a corporation, sole proprietorship, partnership, and/or other legal form if it is ever labeled as such in the 1994-2013 BR. Note that of all the legal types, entrepreneurs at corporations are most likely to be true firm owners; owners of sole proprietorship and partnerships are generally not supposed to take wage and salary income and thus should not appear in the LEHD.

Table A.14: Intensive margin spillovers are similar when entrepreneurs only include top earners

	Dependent Variable: Entrepreneurial Firm Outcome					
	Survive to age 2		Survive to age 5		Entry year log(payroll)	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of coworkers with entrepreneurship	-0.018***	-0.041***	-0.036***	-0.063***	-0.408***	-0.305***
	(0.005)	(0.018)	(0.007)	(0.008)	(0.016)	(0.020)
Share of coworkers with entrepreneurship and survived to age 2		0.024				
		(0.019)				
Share of coworkers with entrepreneurship and survived to age 5				0.044***		
				(0.008)		
Mean entry year log(payroll) of coworkers with entrepreneurship						0.036***
						(0.002)
Model (4) controls	x	x	x	x	x	x
$\mathbb{1}\{0$ entr. coworkers$\}$					x	x
Mean(dep var)	0.789	0.789	0.514	0.514	10.98	10.98
N	640,500					

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence of intensive margin spillovers when I only consider the top earners (as opposed to top 3 earners) at new firms as entrepreneurs. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004 who become entrepreneurs between 2005 and 2009, where entrepreneurship is defined as being the top earner (as opposed to a top 3 earner) at a new firm. The columns present estimates of versions of model (9) for different entrepreneurial firm outcomes, including survival to age 2 (columns 1 and 2) and age 5 (columns 3 and 4) and entry year (age 1) log payroll (columns 5 and 6), with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). In column 2, I add as a covariate the share of coworkers who were recently entrepreneurs and whose firms survived to a second year; in column 4, I similarly add the share who were entrepreneurs and survived to a fifth year. In column 6, I add the mean entry year log payroll of entrepreneurial coworkers; if the individual has no entrepreneurial coworkers, I replace this value with the mean and control for this. Note that the model (4) controls are adapted such that the individual's own recent entrepreneurship is also based on entrepreneurship defined as being the top earner at a new firm. Standard errors are robust and clustered at the establishment level. Mean (std dev) of the share of coworkers who were recently entrepreneurs is 0.029 (0.098); mean (std dev) of the share of coworkers who were recently entrepreneurs and whose firms survived to age 2 or age 5 are 0.025 (0.094) and 0.011 (0.098) respectively. Mean (std dev) of entrepreneurial coworkers' mean entry year log payroll (adjusted for missing values) is 10.84 (1.115).

Table A.15: Extensive margin spillovers predict entrepreneurship in each of the subsequent years

	Dependent Variable: Entrepreneur in				
	2005	2006	2007	2008	2009
	(1)	(2)	(3)	(4)	(5)
Share of coworkers with entrepreneurship	0.008***	0.006***	0.004***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Model (4) controls	x	x	x	x	x
Mean(dep var)	0.007	0.008	0.007	0.006	0.004
N			46,680,000		

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that exposure to entrepreneurial coworkers predicts entrepreneurship in each of the five subsequent years. The table presents regression estimates of an adapted version of model (4) performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004, with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). This table adapts model (4) by replacing the dependent variable with indicators for becoming an entrepreneur (for the first time between 2005 and 2009) in each year, 2005 through 2009 (note these are mutually exclusive from each other). Standard errors are robust and clustered at the establishment level.

Table A.16: Evidence against alternative hypotheses: Spawning, exposure to leaders, and workplace culture

Dependent Variable:	# Entrepreneurs	Co-entrepreneur	Entrepreneur 2005-2009		
Sample	Future entr.		Main		Leave in 2004
	(1)	(2)	(3)	(4)	(5)
Share of coworkers with entrepreneurship	-0.085***	-0.003		0.015***	0.040***
	(0.005)	(0.004)		(0.001)	(0.001)
Share of coworkers with top 3 earnings at any firm			0.032***	0.005***	
			(0.000)	(0.000)	
Model (4) controls	x	x	x	x	x
Mean(dep var)	2.046	0.241	0.034	0.034	0.041
Mean(share)	0.064	0.064	0.034	0.034	0.036
Std dev(share)	0.147	0.147	0.095	0.095	0.094
Mean(share top 3 at any firm)			0.156	0.156	
Std dev(share top 3 at any firm)			0.200	0.200	
N	1,456,000	1,456,000	46,680,000	46,680,000	13,030,000

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence against several alternative mechanisms (coworkers bringing along individuals on their next venture, teaching general leadership skills, or driving individuals to leave the firm) that could explain the extensive margin spillovers. The table presents regression estimates of versions of model (4) performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004 (columns 3-4), the subsample of individuals who become entrepreneurs between 2005 and 2009 (columns 1 and 2), and the subsample of individuals whose last year at the firm is 2004 (column 5); with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). In columns 1 and 2, the dependent variable is different; in column 1, the dependent variable is the number of entrepreneurs (between 1 and 3, only counting those who appear in the data in 2004) at a future entrepreneur's entrepreneurial firm. In column 2, the dependent variable is an indicator equal to 1 if at least one of the other entrepreneurs (if there are any) at an future entrepreneur's firm was employed at the same establishment in 2004, and 0 otherwise. Standard errors are robust and clustered at the establishment level.

Table A.17: Extensive margin spillovers are strongest for top three quartiles of earners

	Dependent Variable: Entrepreneur 2005-2009 (1)	(2)
Share of coworkers with entrepreneurship	0.008***	-0.001
× Earnings in lowest quartile	(0.001)	(0.001)
Share of coworkers with entrepreneurship	0.031***	0.015***
× Earnings in second lowest quartile	(0.001)	(0.001)
Share of coworkers with entrepreneurship	0.030***	0.052***
× Earnings in second highest quartile	(0.001)	(0.001)
Share of coworkers with entrepreneurship	0.038***	0.037***
× Earnings in highest quartile	(0.001)	(0.001)
Model (4) controls	x	x
Earnings quartile FE	x	x
Quartile relative to	Economy	Establishment
N	46,680,000	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that extensive margin spillovers are commonplace across the earnings distribution. The table presents regression estimates of model (4) performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004, with the share variable broken out into mutually-exclusive bins based on the individual's 2004 earnings quartile (either relative to the whole economy, in column 1, or their establishment, in column 2) with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). Standard errors are robust and clustered at the establishment level. For relative to the economy, mean (std dev) of share with entrepreneurship and . . . lowest quartile is 0.009 (0.053); second lowest is 0.010 (0.057); second highest is 0.008 (0.048); and highest is 0.006 (0.039). For relative to the establishment, mean (std dev) of share with entrepreneurship and . . . lowest quartile is 0.007 (0.036); second lowest is 0.010 (0.061); second highest is 0.008 (0.041); and highest is 0.010 (0.057).

Table A.18: Exposure to more entrepreneurs does not predict becoming publicly-traded

Dependent variable:	Publicly-traded within 5 years (1)	(2)	Ever publicly-traded (3)	(4)
Share of coworkers with entrepreneurship	-0.0003	-0.0002	-0.0004	-0.0003
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Model (4) controls	x	x	x	x
Entr. industry FEs		x		x
Mean(dep var)	0.0010	0.0010	0.0014	0.0014
N	1,456,000			

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that exposure to entrepreneurial coworkers predicts less successful firms, by the extreme outcome of being publicly-traded. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments who become entrepreneurs between 2005 and 2009. The columns present estimates of (9) for whether a firm becomes publicly-traded (IPO's, i.e., appears in the CSB) within 5 years after entry (columns 1 and 2) or ever (up until 2016, columns 3 and 4), with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). Standard errors are robust and clustered at the establishment level.

Table A.19: Entrepreneurs who worked with more entrepreneurial coworkers tend to be more self-funded, not family owned, and less innovative

	Dependent Variable: Entrepreneurial Firm Outcome									
	Start-up funding sources			Current funding sources					Family Owned	Patent/ copyright/ trademark
	VC	Banks	Family/ friends	Investors	Banks	Grants	Family/ friends	Owner		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Without entrepreneurial firm industry fixed effects										
Share of coworkers with entrepreneurship	0.008	-0.013	0.014	0.007	-0.022	-0.010	0.007	0.030*	-0.051***	-0.029***
	(0.005)	(0.015)	(0.012)	(0.012)	(0.018)	(0.011)	0.016)	(0.016)	(0.017)	(0.013)
Model (4) controls	x	x	x	x	x	x	x	x	x	x
Year-Entry year FE	x	x	x	x	x	x	x	x	x	x
Panel B: With entrepreneurial firm industry fixed effects										
Share of coworkers with entrepreneurship	0.006	-0.014	0.013	0.005	-0.025	-0.009	0.006	0.032**	-0.052***	-0.025*
	(0.005)	(0.015)	(0.012)	(0.012)	(0.018)	(0.011)	(0.016)	(0.016)	(0.017)	(0.013)
Model (4) controls	x	x	x	x	x	x	x	x	x	x
Year-Entry year FE	x	x	x	x	x	x	x	x	x	x
Entr. industry FE	x	x	x	x	x	x	x	x	x	x
Mean(dep var)	0.025	0.308	0.109	0.130	0.590	0.096	0.274	0.682	0.376	0.209
N	49,000									

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence against several potential mechanisms behind the entrepreneurial spillovers, including financing, family connections, and technological knowledge transfers. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments who become entrepreneurs of firms that are surveyed in the 2014-2016 ASE. The columns present estimates of (9) for different ASE binary outcomes, with controls indicated in the footers (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure); "Year-Entry year FE" indicates fixed effects of the interaction between the year I measure an individual's exposure to entrepreneurial coworkers and the subsequent year the individual becomes an entrepreneur. Panel B includes 6-digit industry fixed effects for the entrepreneur's entrepreneurial firm (at entry). Columns 1-3 present estimates for the sources of the firms' start-up funding, namely whether a firm received funding from venture capitalists (VC), business loans from banks, or business loans from family or friends Columns 4-8 present estimates for the sources of the firms' current funding, including from outside investors (angel investors, VC, or other businesses), banks, government grants, family or friends, and the owner themself. Column 9 presents the estimate for whether the firm is family owned (i.e., whether two or more members of one family own a majority of the firm); column 10 presents the estimate for whether the firm owns any patents, copyrights, or trademarks. See Section A.I.4 for precise definitions of the outcomes. Standard errors are robust and clustered at the establishment level. Mean (std dev) of share: 0.066 (0.151).

Table A.20: Entrepreneurial coworkers push entrepreneurs towards some sectors, away from others

	Dependent Variable: Entrepreneurial Firm in Sector									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Agriculture		Mining		Utilities		Construction		Manufacturing	
Share of coworkers with entrepreneurship	0.001***	0.001***	0.000	0.000	-0.000	-0.000	0.000	-0.004**	-0.004***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
Share of coworkers with entr. in sector (not estab.'s)		-0.007		-0.009***		-0.001		0.293***		-0.041
		(0.004)		(0.003)		(0.002)		(0.027)		(0.037)
Mean(dep var)	0.004	0.004	0.003	0.003	0.007	0.007	0.142	0.142	0.041	0.041
	Wholesale		Retail		Transport/Warehous.		Information		Finance/Insurance	
Share of coworkers with entrepreneurship	0.006***	0.008***	0.002	0.002	0.000	0.001	-0.001	-0.000	0.003**	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share of coworkers with entr. in sector (not estab.'s)		-0.095***		0.012		-0.047***		-0.035***		-0.097***
		(0.017)		(0.020)		(0.008)		(0.008)		(0.012)
Mean(dep var)	0.051	0.051	0.112	0.112	0.033	0.033	0.015	0.015	0.046	0.046
	Real Estate/Licensing		Pro/Sci/Tech Serv.		Management		Admin		Education	
Share of coworkers with entrepreneurship	0.001	0.003**	-0.000	-0.004**	0.001**	0.001***	-0.003**	-0.001	-0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Share of coworkers with entr. in sector (not estab.'s)		-0.115***		0.269***		-0.020***		-0.101***		-0.048***
		(0.012)		(0.024)		(0.001)		(0.014)		(0.005)
Mean(dep var)	0.044	0.044	0.131	0.131	0.003	0.003	0.063	0.063	0.012	0.012
	Health		Arts/Entertainment		Accomm./Food		Other Services			
Share of coworkers with entrepreneurship	-0.003**	-0.003*	0.001*	0.002**	-0.006***	-0.008***	0.000	0.000		
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)		
Share of coworkers with entr. in sector (not estab.'s)		-0.054***		-0.045***		0.126***		0.013		
		(0.013)		(0.008)		(0.017)		(0.013)		
Mean(dep var)	0.097	0.097	0.020	0.020	0.113	0.113	0.072	0.072		
Model (4) controls	x	x	x	x	x	x	x	x	x	x
N	1,456,000									

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that exposure to entrepreneurial coworkers may predict in which sector an individual starts a firm, particularly if those coworkers ran firms in those sectors, suggesting that some spillovers may convey industry-specific information. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004 who become entrepreneurs between 2005 and 2009. The columns present estimates of versions of model (9) for whether the entrepreneurs start firms in each sector, with controls indicated in the footer ((model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). Even columns add as a covariate the share of coworkers who were entrepreneurs in the given column's sector *if* the individual's 2004 establishment is not in that sector (and 0 otherwise). Standard errors are robust and clustered at the establishment level. Mean (std dev) of share of coworkers with entrepreneurship is 0.064 (0.147).

Table A.21: Entrepreneurial exposure predicts higher-paying and lower-inequality entrepreneurship, but this is connected to firm size

	Dependent Variable: 2005-2009 Entrepreneurial Entry Year Firm Pay					
	Mean(Log(Earnings))		Var(Log(Earning))		90-10(Log(Earning))	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of coworkers with entrepreneurship	0.111***	-0.003	-0.179***	-0.020**	-0.327***	-0.005
	(0.007)	(0.007)	(0.010)	(0.009)	(0.011)	(0.008)
Entry year log(employment)		-0.297***		0.418***		0.845***
		(0.001)		(0.001)		(0.001)
Model (4) controls	x	x	x	x	x	x
Mean(dep var)	8.884	8.844	1.507	1.507	2.513	2.513
N	1,456,000					

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that exposure to entrepreneurial coworkers predicts higher paying, less unequal firms, but this patterns is largely driven by the fact that the exposure also predicts smaller firms. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments who become entrepreneurs between 2005 and 2009. The columns present estimates of (9) for different measures of entry year firm pay, with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). Standard errors are robust and clustered at the establishment level. Mean (std dev) of the share is 0.064 (0.147); mean (std dev) of entry year log(employment) is 1.928 (1.199).

Table A.22: Entrepreneurs who worked with more entrepreneurial coworkers tend to run better-managed firms in manufacturing

	Dependent Variable: Entrepreneurial Firm Management Score					
	Overall		Monitoring/Targeting		Incentives	
Sample: Entrepreneurial year	2000-2010	2010	2000-2010	2013	2000-2010	2010
	(1)	(2)	(3)	(4)	(5)	(6)
Share of coworkers with entrepreneurship	0.041*	0.233*	0.044*	0.294*	0.046	0.197
	(0.024)	(0.134)	(0.027)	(0.158)	(0.034)	(0.167)
Model (4) controls	x	x	x	x	x	x
Year-Entry year FE	x		x		x	
Mean(dep var)	0.592	0.595	0.619	0.630	0.553	0.553
Mean(share)	0.044	0.030	0.044	0.030	0.044	0.030
Std dev(share)	0.113	0.064	0.113	0.064	0.113	0.064
N	4,400	300	4,400	300	4,400	300

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents evidence that, unlike in general (see Table A.23), entrepreneurial spillovers may convey some managerial skills for individuals who start firms in the manufacturing sector. The table presents regressions performed on two samples of individuals age 20-64 at 2+ employment establishments who become entrepreneurs of firms that are surveyed in the 2010 MOPS. In odd columns, I include individuals working between 1999 and 2010 (when I observe coworkers) who become entrepreneurs within five years (or by 2010). In even columns, I include individuals working between 2005 and 2009 who become entrepreneurs in 2010; I make this restriction to combat any biases due to selection into survival (as shown in Section IV, exposure to entrepreneurs predicts shorter-surviving entrepreneurial firms). The columns present estimates of (9) for different measures of management structure (the overall management score; the monitoring score; and the incentives score), with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). "Year-Entry year FE" indicates fixed effects of the interaction between the year I measure an individual's exposure to entrepreneurial coworkers and the subsequent year the individual becomes an entrepreneur. Standard errors are robust and clustered at the establishment level.

Table A.23: Entrepreneurs who worked with more entrepreneurial coworkers tend to run worse-managed firms

	Dependent Variable: Entrepreneurial Firm Management Score								
	Overall			Monitoring/Targeting			Incentives		
Sample: Entrepreneurial year	2000-2013		2013	2000-2013		2013	2000-2013		2013
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share of coworkers with entrepreneurship	-0.026***	-0.026***	-0.016	-0.016*	-0.017*	-0.011	-0.051***	-0.048***	-0.006
	(0.009)	(0.009)	(0.022)	(0.010)	(0.010)	(0.023)	(0.016)	(0.016)	(0.039)
Model (4) controls	x	x	x	x	x	x	x	x	x
Year-Entry year FE	x	x		x	x		x	x	
Entr. industry FE		x			x			x	
Mean(dep var)	0.542	0.542	0.533	0.507	0.507	0.499	0.596	0.596	0.583
Mean(share)	0.066	0.066	0.061	0.066	0.066	0.061	0.066	0.066	0.061
Std dev(share)	0.151	0.151	0.150	0.151	0.151	0.150	0.151	0.151	0.150
N	49,000	49,000	8,800	49,000	49,000	8,800	49,000	49,000	8,800

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table present evidence that entrepreneurial spillovers do not convey managerial skills on average. The table presents regressions performed on two samples of individuals age 20-64 at 2+ employment establishments who become entrepreneurs of firms that are surveyed in the 2015 ASE (i.e., the ASE wave that includes questions on management). In columns 1, 2, 4, 5, 7, and 8, I include individuals working between 1999 and 2012 (when I observe coworkers) who become entrepreneurs within five years (or by 2013, i.e., the end of the data). In columns 3, 6, and 9, I include individuals working between 2008 and 2012 who become entrepreneurs in 2013; I make this restriction to combat any biases due to selection into survival (as shown in Section IV, exposure to entrepreneurs predicts shorter-surviving entrepreneurial firms). The columns present estimates of (9) for different measures of management structure (the overall management score; the monitoring score; and the incentives score), with controls indicated in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure). "Year-Entry year FE" indicates fixed effects of the interaction between the year I measure an individual's exposure to entrepreneurial coworkers and the subsequent year the individual becomes an entrepreneur. "Entr. industry FE" indicates the 6-digit industry fixed effects for the entrepreneur's entrepreneurial firm (at entry). Standard errors are robust and clustered at the establishment level.

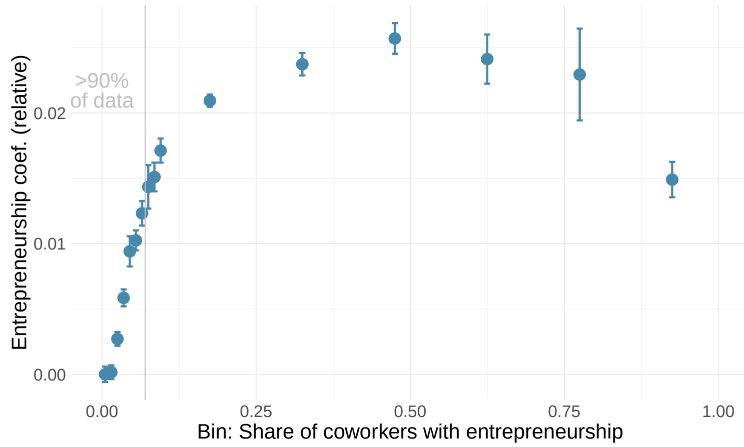
Table A.24: Successful and high-earning entrepreneurial coworkers may dissuade unsuccessful entrepreneurship

Dependent Variable:	Entrepreneur 2005-2009			Entrepreneur 2005-2009 and top 10% log(employment)			Entrepreneur 2005-2009 and *not* top 10% log(employment)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share of coworkers with entrepreneurship	0.025***	0.024***	0.025***	-0.005***	-0.007***	-0.005***	0.029***	0.030***	0.030***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Share of coworkers with entr. and top 10% log(employment)		0.021***			0.032***			-0.011***	
		(0.002)			(0.001)			(0.002)	
Share of coworkers with entr. and earn above $100k			0.006***			0.017***			-0.010***
			(0.002)			(0.001)			(0.002)
Model (4) controls	x	x	x	x	x	x	x	x	x
Share of coworkers earn above $100k			x			x			x
Mean(dep var)	0.031	0.031	0.031	0.005	0.005	0.005	00.026	0.026	0.026
N					46,680,000				

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

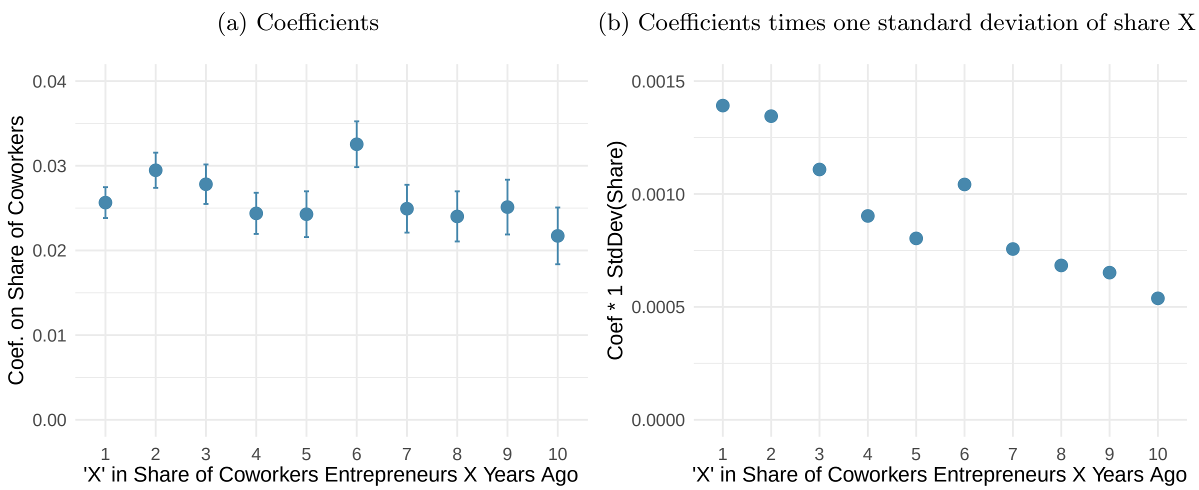
Note: This table presents evidence that particularly successful or high-earning entrepreneurial coworkers may dissuade entrepreneurial ventures that are unlikely to succeed, consistent with the negative spillovers estimated by Lerner and Malmendier (2013), in the context of spillovers across Harvard MBA classmates. The table presents regressions performed on the sample of individuals age 20-64 at 2+ employment establishments. The columns present estimates of several adaptations of model (8) with different controls, as noted in the footer (model (4) controls are log establishment employment, own recent entrepreneurship, demographics, log earnings, and age, industry, and state fixed effects measured at the time of exposure), and measures of entrepreneurial coworkers' success. "Share of coworkers with entr. and top 10% log(employment)," is the share of coworkers who were recently entrepreneurs and whose entrepreneurial firms was in the top 10% of entry year log employment, amongst firms that entered in the same year and industry; "Share of coworkers with entr. and earn above $100k" is the share of coworkers who were recently entrepreneurs and who earn above $100,000 at the firm in 2004 (in 2010 USD). Column 1 presents the main baseline results from Table 3 for comparison. Mean (std dev) of share of coworkers with entrepreneurship is 0.034 (0.095).

Figure A.1: Extensive margin spillovers are concave in exposure to entrepreneurial coworkers



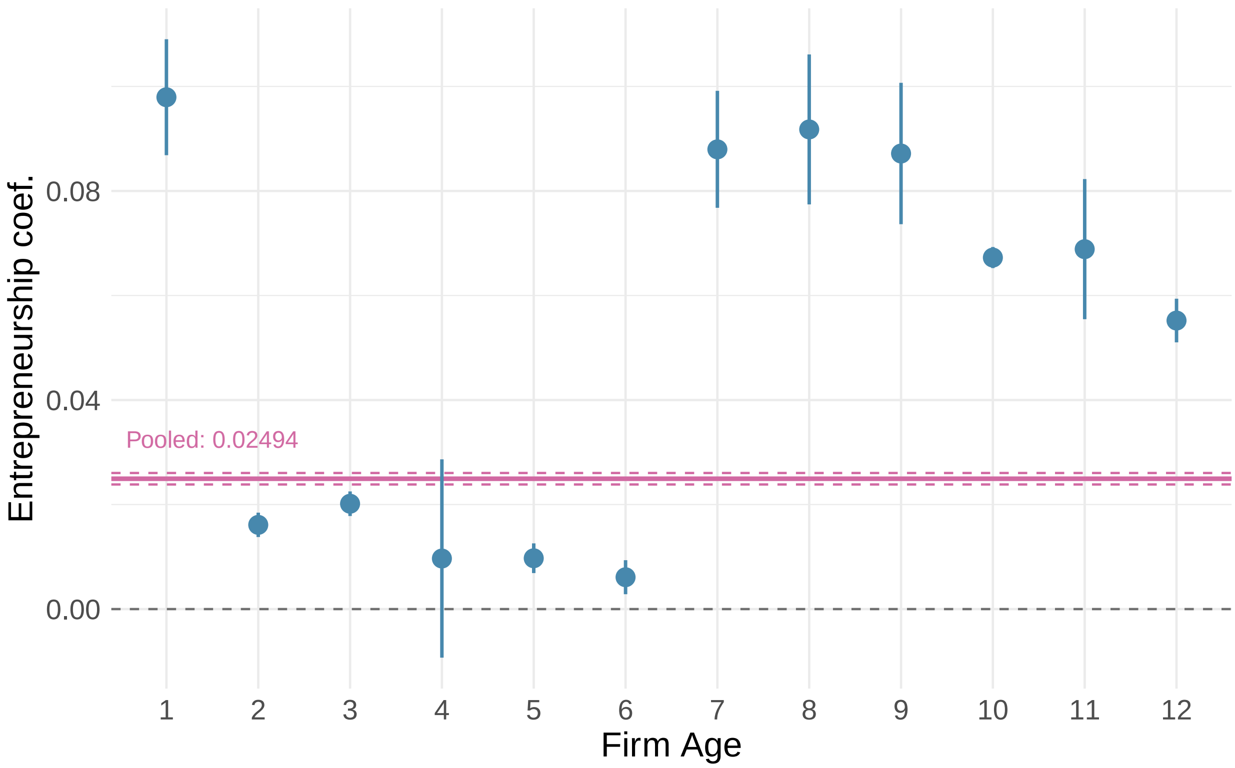
Note: This figure demonstrates that the relationship between an individual's future entrepreneurship and their exposure to entrepreneurial coworkers, conditional on controls, is linear for the majority of the distribution of exposure and generally concave. The figure presents the estimated coefficients from binscatter version of model (4), where the share of coworkers with entrepreneurial experience is replaced by indicators for having the share fall in different bins, e.g., between 0 and 0.01, 0.01, and 0.02, etc; the omitted bin is the indicator for having the share equal to zero. The coefficients are normalized against the first bin, such that the first bin plotted takes on a coefficient of zero. The vertical line indicates that over 90% of individuals have a share of coworkers with entrepreneurial experience lower than 7 percentage points.

Figure A.2: Extensive margin spillovers are marginally higher from more recent entrepreneurship



Note: This figure presents evidence that extensive margin spillovers are similar regardless of how recent the entrepreneurship of the coworkers was. The figure presents coefficient and 95% confidence interval estimates of model (4), where the share of coworkers with entrepreneurial experience is separated into separate variables by when the (most recent) entrepreneurship occurred (1-10 years ago), performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004, including all controls (akin to column (8) of Table 3). Panel A presents the coefficients. Panel B multiplies the coefficients by one standard deviation of the given variable; there is more variation in the share of coworkers who were more recently entrepreneurs, leading to large value for the exposure to more recent entrepreneurs.

Figure A.3: Entrepreneurial spillovers vary by firm age



Note: This figure presents evidence that the extensive margin spillovers are not driven by individuals at firms of particular ages. The figure presents regression coefficient and 95% confidence interval estimates of an adapted version of model (4), performed on the sample of individuals age 20-64 at 2+ employment establishments in 2004, in which I replace the explanatory variable (share of coworkers who were entrepreneurs in the past 5 years) with the share of coworkers who were entrepreneurs in the past 5 years interacted with the individual's 2004 firm's age (age based on LEHD employment, censored at age 12); I also control for firm age fixed effects.