A Theory of Silicon Valley

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Abstract

This paper presents a model of the software-focused, venture-backed entrepreneurship found in the San Francisco Bay Area, or "Silicon Valley." Three kinds of markets matter in the model: (1) the financial market for venture capital, (2) the labor market for engineers, and (3) the collection of product markets successful technology companies serve. The key economic actors are elite "engineers" who decide between employment and entrepreneurship. Wages clear the labor market; retained equity clears the venture capital market. The model predicts the equilibrium startup probability of success, startup valuations, engineer wages, the returns to entrepreneurship and the split of engineers between entrepreneurship and employment. What affects the equilibrium are the direct cost of doing a startup, the cost of capital, the extent of product markets, the supply of engineers, and the innovation "environment." In addition to presenting the theory, I also introduce a novel dataset on the career trajectories of paradigmatic elite engineers—Stanford Computer Science PhD graduates—to illustrate some of the stylized facts motivating the model.

JEL: J24, O30

1 Introduction

Silicon Valley entrepreneurship follows a pattern: an entrepreneur founds a startup, hoping to succeed in some product market. She needs seed capital, and so she sells equity to venture capitalists (VCs). Expected profits from her startup depend on the viability of her business idea, the degree of competition she faces, her execution, the size of the product market, and the cost of "scaling" the startup. A major component of those scaling costs are labor costs from hiring engineers. If she succeeds, she earns a profit proportional to how much equity she was able to retain, with rest going to her VC investors.

While I call the pattern above "Silicon Valley entrepreneurship," there is seemingly little that distinguishes it from entrepreneurship more generally, except perhaps for the role played by VCs. One distinguishing feature is that the product itself is usually software or heavily software-dependent, as modern Silicon Valley has moved away from its hardware-focused roots (Arora et al., 2013). As such, the engineers hired to scale the startup are primarily software engineers. But a close inspection of many Silicon Valley entrepreneurial ventures reveals that entrepreneur is also very likely to be a software engineer.
degree in computer science from an elite university is the de rigeur background for both engineers and the founding entrepreneurs.

There are several possible explanations for why entrepreneurs and engineers are drawn from the same pool. Perhaps an engineering background is needed to appreciate which ideas are technical viable. Or perhaps no one is willing to fund an idea or join a startup as an employee without a prototype, and building a prototype requires engineering skills. For example, it is hard to imagine Mark Zuckerberg obtaining VC funding without a functioning early version of Facebook that already had users. Whatever the reason, my claim is that this stylized fact is essential to understanding Silicon Valley entrepreneurship.

In this paper I develop a model of Silicon Valley entrepreneurship, by which I mean the venture-backed, software-focused entrepreneurship found primarily in the San Francisco Bay Area (Guzman and Stern, 2015). The key economic actor in the model is the engineer, who chooses between employment and entrepreneurship. The relative returns to each career choice depend on the choices made by other engineers: more engineers choosing employment lowers wages by increasing supply in the labor market; more engineers choosing entrepreneurship lowers success probabilities and makes terms from VCs less favorable. In equilibrium, the marginal engineer is indifferent between employment and entrepreneurship.

Section 2 lays out the model assumptions and derives an equilibrium. Startups are founded by engineers who must sell equity in their companies to obtain funds. Each startup pursues a single business idea. These ideas are nonrivalrous and any engineer is free to pursue them. Critically, many engineers can pursue the same idea. There is no “market for ideas” and so in the Gans and Stern (2003) framework, would-be technology entrepreneurs have to choose product market competition as their commercialization strategy (rather than licensing). ¹ This modeling approach is justified by several stylized facts about software-focused technology entrepreneurship: patents are difficult to enforce, (technical) imitation is relatively easy and the control over specialized complementary assets often non-existant (particularly with the rise of Internet undercutting the importance of the maker of the operating system or physical distribution channels).

If an idea is pursued by at least one entrepreneur-engineer, the world learns if that idea “works,” in the sense that it leads to a viable product market. All successful ideas have an idea-specific product market independent of all other product markets. The probability that an idea will be successful is known publicly ex ante, and so “good” ideas attract more entrants until the expected returns to all ideas are the same.

Product markets are winner-take-all, and only one of the entrepreneur-engineers pursuing the idea associated with that product market is ultimately successful. This assumption about product markets creates the quasi-rents needed to induce engineers to pursue entrepreneurship. Successful entrepreneur-engineers gets profits proportional to the amount of their original equity they were able to keep, with VCs getting the rest. Profits are determined by the size of the product market as well as the cost of engineer labor, which in turn depends on the fraction of the engineer labor force that chooses employment.

The key exogenous factors in the model are the cost of founding a startup, the size of the product market, the supply of engineers and the innovation “environment,” which can be thought of as the supply of available startup ideas. The cost of founding a startup includes direct costs related to the state of technology and the cost of living for engineer-entrepreneur, as well as the cost of financing the investment. The model makes predictions about startup valuations, engineer wages, the equity retained

¹See Gans et al. (2002) for the implications of an environment that leads to this kind of “product market or bust” form of technical entrepreneurship.
by engineer-entrepreneurs, the startup probability of success and the fraction of engineers engaged in entrepreneurship.

Section 3 derives the model predictions about the effects of changes in startup costs. The model predicts that a decrease in startup costs (technological, financial, living expenses etc.) raises engineer wages and retained equity, reduces startup success probability, and raises expected profits but lowers realized profits. A decrease in startup costs also shifts more engineers towards entrepreneurship. Comparative statics about startup costs are useful in that startup costs are frequently “shocked” by technology (or are shock-able through public policy). For example, the rise of Amazon Web Services (AWS) eliminated the need for startups to run their own data centers, which is thought to have substantially lowered startup costs. On the financial side, low interest rates, the rise of angel investing and the rise of crowdfunding has lowered capital costs in recent years. However, moving costs in the opposite direction, the price of housing in Silicon Valley has also increased enormously.

An ubiquitous question about Silicon Valley is whether it is “in a bubble” in that startups on-paper valuations have deviated from some fundamental value. Rising startup valuations is often cited as evidence for a bubble. Another supposed piece of evidence is the ideas startup pursue—many are accused of pursuing slight variations on some existing idea rather than engage in “deep” innovation. Or that they are pursuing obviously “bad” ideas. My model has something to say about all of these concerns. By predicting startup valuations, the model speaks to the ubiquitous “bubble question” by characterizing a startup's fundamental value. On the ideas startups pursue, so long as startups are free to pursue any idea, when startup cost are low (which raises implied valuations), there is excess entry on ex ante good ideas and ex ante worse ideas get funded.

Section 4 derives the model predictions about how a change in the supply of engineers affects the equilibrium. An increase in the supply of engineers lowers engineer wages, reduces retained equity, reduces startup success probability and lowers expected profits but raises realized profits, conditional upon a success. Whether a supply increase of engineers is biased towards entrepreneurship or employment depends on the elasticity of demand for engineers in the labor market. In a nutshell, when the labor market can readily absorb new engineers with little decrease in wages (i.e., labor demand is elastic), then new entrants are biased towards employment and vice versa when demand is inelastic. The supply of engineers is strongly affected by government policy, through its funding of STEM education (in the long run) and policies on high-skilled immigration (in the short run). Land prices also affects the supply of engineers and startup costs.

Section 5 focuses on the effects of changes in the innovation environment. Changes in the stock of ideas have effects similar to changes in engineer supply. More ideas raise wages, raise retained equity, raise startup success probability and raise expected profits, but lower realized profits. More ideas have an ambiguous effect on entrepreneurship: although there are better ideas to pursue (raising the startup success probability), there are also more successful firms, each demanding engineer labor, which drives up wages.

Section 6 describes the effects of changes in the size of product markets. An increase in the size of product markets raises wages and retained equity and lowers the startup success probability. Expected and realized profits rise. Despite the larger product markets increasing demand for labor and leading to higher wages, the fraction of engineers pursuing entrepreneurship increases.

Although my theory of Silicon Valley is novel, there is a body of literature on Silicon Valley that explores some of the “pieces” of my model. Extant work on Silicon Valley has focused on attributes that make it distinctive. Factors that have been cited include: a deep, highly mobile pool of technical talent

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2For example, a website that lets people rent out their homes to strangers from the Internet.
(Fallick et al., 2006); a well-established and risk tolerant venture capital industry; proximity to major re-
search universities (Jaffe, 1989); and even cultural differences more favorable to innovation (Saxenian,
1996). While clearly important, these disparate explanations have little to say about how changes in key 
factors—such as the state of technology, the cost of capital, the size of the engineer workforce and the 
product market for what Silicon Valley produces—will affect outcomes like the wages of engineers, the 
equity retained by entrepreneurs and the number and quality of startups that receive funding.

As with all models, my assumptions drive the results. In the Friedman view of economic methodol-
gy, these assumptions are “off limits” to investigation, and what matters is the predictive power of the 
theory (Friedman, 1953). In this view, my assumption that the marginal engineer is de facto risk neutral 
is not worthy of empirical inquiry, just as we would not ask a businessman whether they produce until 
marginal cost equals price. While this view is liberating from the modeler, it is not necessarily persuas-
ive. As such, Section 7 discusses the modeling assumptions in more depth, with a focus on highlighting 
the germane differences between technological entrepreneurship and other forms of entrepreneurship. 
These differences highlight why assumptions like de facto risk neutrality of engineers is far more plau-
sible in the case of Silicon Valley entrepreneurship. This section also introduces a novel dataset on the 
career trajectories of a sample of PhD graduates from Stanford Engineer’s Computer Science Depart-
ment. The main results are that (1) a remarkably high fraction of graduates have founded companies 
(2) there was a strong shift towards entrepreneurship prior to the dot com boom and (3) graduates fre-
quently move back and forth between entrepreneurship and employment. Section 8 concludes.

2 The Model Setup

A startup is founded by a single engineer, implementing a single idea. The initial direct cost of cre-
at ing this startup is $c$. This cost includes hardware, software, real estate, living expenses and so on. 
Entrepreneur-engineers have no other source of funds, and only a VC can provide seed capital. This 
investment is made once and is an arm’s length investment.4

There are $\kappa$ startup ideas. These ideas are common knowledge, and any entrepreneur-engineer is free 
to use them for her startup. If pursued by a startup, an idea will “work” in the product market defined by 
that idea with probability $q$. This product market success probability $q$ is distributed on $[0, 1]$ with pdf $f$. 
The treatment of ideas is motivated by Kerr et al. (2014), who write, “for entrepreneurs, it can be virtually 
impossible to know whether a particular technology or product or business model will be a success until 
one has actually invested in it.”

An idea with success probability $q$ will attract $n$ entrepreneurs until startup success probabilities are 
equalized across ideas:

$$\frac{q}{n} = q_0,$$

where $q_0$ is the idea success probability of the worst idea pursued. The expected number of startups will

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3 We might think that only VCs have the expertise to know $q$ and that regular capital institutions would be quickly driven out 
of a market by adverse selection. Sorensen (2007) provides a two-sided matching model of venture capital and startup firms. It 
is unclear to what extent “better” VC firms just get a discount relative to those offering less value. This is not matching per se, 
but rather just a compensating differential, with different firms putting different values on what different VC firms offer.

4 This contrasts with Bergemann and Hege (2005), who model funding as a flow rather than a one-off investment. Further, in 
their model, there is investor uncertainty about success probability, which in this model is public knowledge and the same for 
all startups.
Figure 1: The allocation of entrepreneur-engineers over ideas

Notes: This figure shows the number of entrepreneur-engineers per idea before and after an influx of new entrants.

be

\[ N = \kappa \int_{q_0}^{1} \frac{q}{q_0} f(q) \, dq. \]  \hspace{1cm} (2)

Figure 1 shows the number of engineers per idea before and after an increase in the number of entrepreneur-engineers. Note that there is more entry on ex ante better ideas and that the worst idea gets just one engineer-entrepreneur. When the number of entrepreneurs increase, some enter on ideas that were already being pursued, while others pursue previously unexplored ideas. Section 6.1 discusses the breakdown on entrants on new versus already-pursued ideas.

Product market success is independent across ideas, and all product markets have the same characteristics (and are independent of each other). However, each idea—if successful—will only have one product market winner among those startups that pursue that idea: after the entrepreneur-engineer creates the startup, she learns not only whether the idea is successful, but also whether her particular implementation of the idea will beat out all other competitors pursuing that same idea. For all startups, the ex ante probability of winning the product market is thus \( q_0 \), and the expected number of succeeding startups is simply \( q_0 N \). I assume that \( S \) is sufficiently large that engineers choose employment or entrepreneurship as if there would be exactly \( q_0 N \) successful firms. This is not a consequential assumption, in that even if the number of successful firms was a binomial random variable, the resultant engineer wage—which is what both would-be entrepreneurs and employees care about—would converge to a constant as \( S \) grows large while the other aspects of the equilibrium, namely \( q_0 \) and \( g \).

A defining feature of many technology startups is high fixed costs and low (often zero) marginal costs. Software startups also frequently have complex business models and are poorly described by conventional production functions. This is no accident, in that VCs are not interested in funding price-takers but rather hope to spot and fund firms that, if successful, obtain quasi-rents. For software startups, these

\[ 5 \text{To see why, suppose that } N_A \text{ is the realized number of startups and } N_A \sim \text{Binom}(N, q_0). \text{ The result wage would have to satisfy } d(w)N_A = (1-g)S, \text{ and so } w = d^{-1}(X), \text{ where } X = \frac{(1-g)S}{N_A}. \text{ The variance of } X \text{ is } V(X) = \frac{(1-g)^2(1-q_0)}{S^2q_0^2N_A}, \text{ thus } \lim_{S \to \infty} V(X) = 0 \text{ (recall that } q_0 \text{ and } g \text{ are fixed).} \]
quasi-rents are generally not due to patents but often to strong network effects. To avoid modeling these complexities, I assume that for each startup, there is some total addressable product market that offers a maximum revenue of \( R \). The fraction of this revenue actually realized (or the probability that \( R \) is realized) is \( \phi(L) \in [0, 1] \), with \( \phi'(L) > 0 \) and \( \phi''(L) < 0 \) where \( L \) is the number of engineers hired. Profits are

\[
\pi = \arg \max_L \phi(L)R - wL. \tag{3}
\]

The firm chooses \( L^* \) such that \( \phi'(L) = w/R \). The resultant maximized profit is common knowledge among VCs and entrepreneurs. This approach provides the quasi-rents needed to explain entrepreneurial effort but without the complication (and unrealism) of modeling scaling firms as having a demand for labor distorted by monopoly output considerations.

The firm specific demand schedule for engineers is \( d(w) = -\frac{\partial \pi}{\partial w} \). Whether a startup succeeds or fails is common knowledge and verifiable, and so “scaling” costs can be financed with regular, non-VC capital.\(^6\)

In the market for venture capital, the amount of investment sought by entrepreneur-engineers is \( c \); the market is cleared by \( 1 - e \), the share of the startup purchased by the VC (and thus the claim to the profits if the startup succeeds). The expected payoff from being a funded entrepreneur is thus \( eq_0\pi \). For an engineer to be indifferent between working for a scaling startup and founding a startup, the expected payoff from entrepreneurship must equal the market wage, or:

\[
eq_{eq_0}\pi = w. \tag{4}
\]

The VC market is competitive, and all VC firms receive the same expected return on capital, \( r \).\(^7\)

Figure 2 illustrates the successful startup's choice about the optimal number of engineer-employees to hire. They choose a number of engineer-employees such that the marginal revenue equals the marginal cost, which is simply the market wage. This leaves profits of \( \pi = \phi(L^*)R - wL^* \), with a fraction \( e \) of that kept by the engineer-entrepreneur and the rest going to the VCs.

The supply of engineers is fixed and employee-engineers supply labor inelastically on the extensive margin. Although this is a simplification—presumably finding good VCs to review startup pitches is challenging and engineers can be lured to move—the global nature of capital but the localized nature of labor justifies my characterization.\(^6\) More capital can readily and quickly be invested in VC firms and then made available to startups, whereas software engineers take longer to create. Given free entry in the VC market, the return to the capital invested in a startup equals the share of expected profits:

\[
(1 + r)c = (1 - e)q_0\pi. \tag{5}
\]

As the \( (1 + r)c \) term appears frequently but never split into component pieces, for simplicity, let \( C = (1 + r)c \), which is the total startup cost. The ratio of entrepreneur equity to VC equity is the ratio of

\(^6\)Later round investments by VC firms often have this flavor, though this is not their specialty: Gompers (1995) shows that VCs concentrate their investments in high-technology firms with high information asymmetries. In short, they specialize in providing this kind of seed funding and become more of a generic source of scaling capital when the uncertainty is resolved. In my model, uncertainty is resolved all at once, though in reality this is a continuous process.

\(^7\)In a survey of the VC literature, Da Rin et al. (2011) note: “Overall we note that while different studies obtain somewhat different estimates of the net returns, there is an emerging consensus that average returns of VC funds do not exceed market returns.”

\(^8\)Hochberg et al. (2010) provides evidence that suggests VCs with thick networks do block entrants.
Figure 2: Successful startup’s demand for engineer-employee labor

![Diagram of a firm's demand for engineer-employee labor](image)

**Notes:** This figure illustrates the successful firm’s demand for employee-engineer labor. The firm chooses a number of engineers, \( L^* \), such that \( \phi(L)R - wL \) is at an optimum. This generates a profit, which are revenues less labor costs. The profit is split between the entrepreneur-engineer, who gets a share \( e \) and the VCs that get \( 1 - e \).

According to Courant and Kornog, the market wage is

\[
\frac{e}{1-e} = \frac{w}{(1+r)c} = \frac{w}{C}. \tag{6}
\]

The retained equity of an entrepreneur is simply

\[
e = \frac{w}{w+C}. \tag{7}
\]

As startup costs go towards zero, entrepreneur-engineers retain full ownership of their startups. The engineer’s market wage is

\[
w = q_0 \pi - C, \tag{8}
\]

which is the expected profit from a startup, minus the VC’s opportunity costs of financing the idea.

I assume that the “startup” phase happens first, the winners are determined and then the scaling phase occurs. Engineers have to decide whether to participate in the startup phase as entrepreneurs or wait until the scaling phase and become employees of the winners. I assume that engineers have to pick a phase ex ante and that they do not discount the future. Regardless of success, the startup claims one engineer (the entrepreneur)—it also hires \( d(w) \) engineers if it succeeds in the product market, which happens with probability \( q_0 \). For the labor market to clear,

\[
S = N + N q_0 d(w), \tag{9}
\]

\[\text{Obviously it takes time for an actual startup to learn about its success in the product market, but for technology companies, this time-line is often remarkably compressed. And while the actual formation of companies is continuous, adding a more realistic time component would complicate the model without necessarily enhancing insight.} \]
and thus the fraction of the engineering labor force engaged in entrepreneurship is

$$g = \frac{N}{N + q_0 N d(w)} = \frac{1}{1 + q_0 d(w)}. \quad (10)$$

This is the ratio of engineers needed for a startup ex ante to the expected number engineers needed by a startup ex post. When considering comparative statics related to entry into entrepreneurship, we can simply evaluate the effect on $q_0 d(w)$.

### 2.1 Preliminaries for comparative statics results

Before discussing the comparative statics, I provide two useful lemmas. The first is Lemma 1, which shows that $w$ and $q_0$ move in opposite directions for all shocks (except those to the supply of engineers and/or the innovation environment). The second is Lemma 2, which relates the wages of engineers to changes in the supply of engineers and the supply of startup ideas.

**Lemma 1.** Any small change in an exogenous (with respect to $S$ and $\kappa$) variable that raises $w$ decreases $q_0$ and vice versa.

**Proof.** The labor market clearing condition in Equation 9 can be written as

$$d(w) = \frac{S}{\kappa} \int_{q_0}^{1} q f(q) d q - \frac{1}{q_0}. \quad (11)$$

Let $\gamma$ be some exogenous variable that does not affect $\kappa$ or $S$ but does affect $w$ and $q_0$. If we differentiate the market clearing condition by $\gamma$ we have

$$d'(w) \frac{\partial w}{\partial \gamma} = \frac{\partial q_0}{\partial \gamma} \left( \frac{1}{q_0} + \frac{S f(q_0) q_0^3}{\kappa \left( \int_{q_0}^{1} q f(q) d q \right)^2} \right) \frac{1}{q_0^2}. \quad (12)$$

On the right-hand side, the last two factors are both positive. And since $d'(w) < 0$, $\frac{\partial w}{\partial \gamma}$ and $\frac{\partial q_0}{\partial \gamma}$ have opposite signs. \hfill \Box

**Lemma 2.** Engineer wages are decreasing the ratio of engineers to ideas.

**Proof.** Let the ratio of engineers to startup ideas be $a = S/\kappa$. Using Equation 9, we can write labor demand as

$$d(w) = \frac{1}{f_{q_0}^{1} q f(q) d q} - \frac{1}{q_0}. \quad (13)$$

Differentiating with respect to $a$, we have

$$d'(w) \frac{\partial w}{\partial a} = \frac{1}{f_{q_0}^{1} q f(q) d q} + \frac{\partial q_0}{\partial a} \left( \frac{1}{q_0^2} + \frac{af(q_0)}{\left( \int_{q_0}^{1} q f(q) d q \right)^2} \right). \quad (14)$$

Assume that $\frac{\partial w}{\partial a} > 0$. Since $d'(w) < 0$, the entire right-hand side must be negative, which implies that $\frac{\partial q_0}{\partial a} < 0$. However, if we differentiate the expression for employee wages, Equation 8, by $a$, we get

$$\frac{\partial w}{\partial a} (1 + d(w) q_0) = \pi \frac{\partial q_0}{\partial a}, \quad (15)$$

which implies that $\frac{\partial w}{\partial a}$ and $\frac{\partial q_0}{\partial a}$ have the same sign, contra our original assumption. Therefore, $\frac{\partial w}{\partial a} < 0$. \hfill \Box
3 Startup costs

When the cost of doing a startup rises, entrepreneurs require more capital and have to give up more equity to obtain it. This in turn makes employment relatively more attractive, putting downward pressure on wages. The fraction of engineers devoted to entrepreneurship falls and the VC funding standard rises, and so startup success probability rises. The dark side of this greater success probability is that fewer ideas are explored. When startups are cheap, VCs are willing to fund marginally worse startup ideas with lower success probabilities; those VCs are also willing to fund more entrants on the same ideas. Because of this increase in success probability—and the lower wage bill if an idea is successful—both expected and realized profits increase.

Proposition 1. An increase in startup costs: (1) lowers the wages of engineers, (2) lowers the retained equity of entrepreneurs, (3) raise the startup probability of success, (4) raises expected profits, (5) raises realized profits, and (6) reduces the fraction of engineers pursuing entrepreneurship.

Proof. For (1), starting from

\[ C = q_0 \pi - w, \]

and differentiating by \( C \), we have

\[ 1 = \pi \frac{\partial q_0}{\partial C} - (1 + q_0 d(w)) \frac{\partial w}{\partial C}. \] (16)

Assume that \( \frac{\partial q_0}{\partial C} < 0 \). For the equality to hold, it would imply that \( \frac{\partial w}{\partial C} < 0 \), but this is a contradiction by Lemma 1, and therefore \( \frac{\partial q_0}{\partial C} > 0 \) (which is claim (3)), which implies that \( \frac{\partial w}{\partial C} < 0 \) by Lemma 1 (which is claim (1)). For (2), from Equation 7, we know that retained equity falls as well when startup costs increase. For (4), since \( q_0 \) goes up and \( w \) goes down, expected profits, \( q_0 \pi \), go up. For (5), as \( w \) is lower, realized profits go up as well. For (6), since \( w \) goes down, \( d(w) \) goes up, and since from (3), \( q_0 \) goes up, entrepreneurship goes down, by Equation 10.

Figure 3 illustrates the effects of an increase in startup costs. The x-axis is \( g \), the fraction of engineers pursuing entrepreneurship. The wages of engineers as a function of \( g \) is \( w(g) \), which is rising in \( g \), as a higher \( g \) means more successful startups and fewer engineer-employees. Before a change in startup costs, the returns to entrepreneurship are \( (q_0 \pi)(g) - C \), where \( (q_0 \pi)(\cdot) \) should be thought of as a function. In equilibrium, returns are equalized. When \( C \) increase by \( \Delta C \), the entrepreneurship returns curve is shifted down and intersects the wage function at a lower wage: At the new equilibrium, engineer wages are lower, going from \( w \) to \( w' \). The fraction of engineers is also lower, going from \( g \) to \( g' \).

Note that the degree of fall-off in engineer wages (which is, at most, \( \Delta C \)) depends on the steepness of the entrepreneurship returns curve in \( g \). When it is relatively flat, employee-engineers are very “exposed” to changes in startup costs. The curve is flat when additional engineers pursuing entrepreneurship does not lower \( q_0 \) very much (see Section 6.1 for a characterization of how \( q_0 \) is affected by more engineer-engineers) and/or additional engineers pursuing employment does not lower wages very much. The former happens when labor demand is highly elastic. Intuitively, elastic labor demand means that successful startups can readily absorb more employee-engineers with little fall-off in wages. As such, when startup costs rise, engineers readily flow away from entrepreneurship and into employment. The reverse of course is true when startup costs fall—it takes a large movement of engineers into entrepreneurship to lower employee wages.

At least for software entrepreneurship, direct technical costs have undoubtedly fallen in recent years: the rise of open source software and pay-by-usage hosting available from sites like Amazon Web Services have substantially lowered technical costs. The financing environment has also changed, with
Notes: This figure illustrates the effects of an increase in startup costs from $C$ to $C + \Delta C$. This increase shifts the returns to entrepreneurship curve, $[q_0\pi(g) - C]$ down by an amount $\Delta C$. At the new equilibrium, the fraction of engineers pursuing entrepreneurship falls from $g$ to $g'$ and wages fall from $w$ to $w'$.

The growth of angel investors, incubators, crowdfunding and so on, making seed capital more available. While not formally a part of the model, venture capital is released in “series” going from a seed round, to a series A, to a series B, and so on. More readily available seed capital has not been matched by an increase in funds intended for scaling, leading to the so-called “series A crunch.” Although technological direct costs of founding a startup have fallen, other direct costs have risen. For example, the cost of housing in Silicon Valley has risen dramatically.

The existing empirical literature is broadly consistent with the predictions of the model. Gompers and Lerner (2000) show at the VC firm level (not the industry level) that an increase in available funds leads to higher valuations (which in the model is the same as entrepreneurs retaining more equity). This is consistent with competition for a limited number of attractive investments.

Nanda and Rhodes-Kropf (2013) find that VC-backed firms receiving their initial investments in hot markets are more likely to go bankrupt, but (conditional upon going public) are valued higher and have more citations to their patents. They interpret this as VCs investing in riskier and more innovative startups when more capital is available. In the language of my model, the decrease in $C$ (because of more capital available) lowered $q_0$, meaning marginally worse firms get funded and so failures increase. In my model, all startups have the same product market—heterogeneity is in the success probability—but it is not difficult to imagine a variant of the model with heterogeneity in both expected product market profits and startup success probability: we would still get the same “spreading” of entrepreneurs over the joint idea/product market distribution and an influx of funds moving the success probability and expected payoff “frontier” rather than $q_0$. 


4 Supply of engineers

An increase in the supply of engineers lowers equilibrium wages. A supply increase also lowers the VC funding standard, meaning that more speculative ideas are funded. Expected profits fall, but realized profits conditional upon a successful startup increase. A supply increase can either be entrepreneurship-biased or employment-biased.

Proposition 2. An increase in the supply of engineers: (1) lowers the wages of engineers (2) lowers the retained equity of entrepreneurs. (3) lowers expected profits (4) raises realized profits (5) lowers the startup probability of success and (6) has an ambiguous effect on entrepreneurship.

Proof. The lowering of wages result (1) follows from Lemma 2, since \( \frac{\partial a}{\partial S} > 0 \). For (2), from Equation 7, we know that retained equity falls as well since \( \frac{\partial}{\partial w} w > 0 \). For (3), from Equation 8, \( \frac{\partial w}{\partial S} = \frac{\partial}{\partial w} q_0 \pi < 0 \) (making use of the fact that wages fall). For (4), \( \frac{\partial q}{\partial S} = -d(w) \frac{\partial w}{\partial S} > 0 \), as \( d(w) > 0 \) (and again making use of (1)). For (5), from the occupational indifference condition, we know that

\[
\frac{\partial w}{\partial S} = \frac{\partial}{\partial w} [q_0 \pi].
\]

From the envelope theorem, \( \frac{\partial \pi}{\partial S} = -\frac{\partial w}{\partial S} \), and so

\[
\frac{\partial w}{\partial S} (1 + q_0 d(w)) = \pi \frac{\partial q_0}{\partial S},
\]

and since \( \frac{\partial w}{\partial S} < 0 \), \( \frac{\partial q_0}{\partial S} < 0 \). For (6), as \( w \) goes down, \( d(w) \) goes up, but as \( q_0 \) goes down, the overall effect on the entrepreneurship fraction, \( g \) is ambiguous.

An engineer supply shock has an ambiguous effect on the fraction of engineers pursuing entrepreneurship. Consider a shock of engineers, all of whom enter employment, thus lowering the fraction of engineers pursuing entrepreneurship. Engineer wages will fall, making entrepreneurship relatively more attractive. Falling wages also partially get passed through to entrepreneurs as lower labor costs, furthering increasing relative returns to entrepreneurship. However, the degree to which wages fall depend on the elasticity of demand: if demand is highly elastic, then the increase in supply has little effect on wages. To restore the equilibrium, some fraction of the new engineers will choose entrepreneurship instead of employment, with the precise amount depending critically on the elasticity of labor demand.

With some algebra, we can write the condition under which the fraction of engineers devoted to entrepreneurship increases, which is

\[
|\eta^d_w| < \frac{e}{g}.
\]

When \( |\eta^d_w| \) is very small (the demand for labor is inelastic), a shock of engineer-employees will sharply reduce wages, making employment relatively less attractive and entrepreneurship more attractive. If demand is highly elastic—\( |\eta^d_w| \) is large—then the new engineers will quickly be “absorbed” in the labor market with little reduction in wages.

Figure 4 illustrates the importance of labor demand elasticity in determining the effects of a supply shock on entrepreneurship. Assume that there is a positive supply shock, \( \Delta S \) and that the new engineers split in the same entrepreneur and employee proportions as existing engineers. The returns to entrepreneurship go down as the new engineers drive down success probabilities, and the curve shifts...
Figure 4: Engineer supply shock with different labor demand elasticities

Notes: This figure illustrates the role of the labor demand elasticity in determining whether a positive supply shock of engineers will be entrepreneurship-biased or employment-biased. See the discussion of this figure for details.

from \([q_0 \pi; S](g) - C\) to \([q_0 \pi; S + \Delta S](g) - C\). The effects of this shock in the labor market depend on the demand elasticities. The horizontal curve \(w\) corresponds to labor demand curve that is infinitely elastic. The market wage for employee-engineers is completely insensitive to the number of engineers, and thus it does not move vertically following the shock. To restore an equilibrium, some entrepreneurs need to exit entrepreneurship and become employees, thus lowering the fraction devoted to entrepreneurship, which goes from \(g\) to \(g'\).

Now consider the case when labor demand is not perfectly elastic, \(w(g; S)\). With the new engineers, this curve shifts downward by some amount (though less than the “full” effect of the marginal engineers entering employment, since the number of successful startups goes up by some amount due to the new entrepreneur-entrants). As drawn, this new curve \(w(g; S + \Delta S)\) intersects the entrepreneurship returns curve, \([q_0 \pi; S + \Delta S](g) - C\), such that entrepreneurship would rise from \(g\) to \(g''\) to restore an equilibrium. The elasticity of demand for labor depends on the shape of \(\phi(\cdot)\).

The main comparative static results with respect to labor supply are fairly intuitive—increased supply lowers wages. Although supply shocks have not always manifested themselves as wage decreases in various empirical settings (e.g., Card (1990)), for the tech sector, there is more evidence of direct substitutability between new entrants and incumbents: Bound et al. (Forthcoming) find evidence that high-skilled foreign workers are substitutes for their native counterparts. Using a calibrated model, they find that wages did not grow as much following the late 1990s tech boom as would have been expected, suggesting that the influx of immigrants during that period kept wages low. This is consistent with Hunt and Gauthier-Loiselle (2010), who find that when compared to similar natives, immigrants who come to the US for employment or study are comparable in terms of innovation outcomes. (They have a large raw advantage compared to the native population as a whole).

The supply of engineers in the labor market is substantially affected by government policy. Quotas on high-skilled immigration affects the short-run supply, and subsidization for STEM education affect the long-run supply. Immigrants make up a large share of the STEM workforce and consensus estimates
suggest they make up about 25% of the founders of tech companies, though obtaining precise unbiased estimates is challenging (Kerr, 2013).

5 Stock of ideas

The appeal of entrepreneurship rises when more startup ideas are available, which in turn raises the wages of employee-engineers and increases the fraction of equity retained by entrepreneur-engineers. The startup success probability also increases, as there are more ideas to choose from and relatively better ideas get pursued. It is important to note that when there are more ideas, exploration goes down in the sense that entrepreneurs can be pickier about which ideas get pursued. The increase in the stock of ideas has an ambiguous effect on entrepreneurship, as the increases startup success probability increases the number of successful firms, each of which demands engineer labor.

**Proposition 3.** An increase in the stock of startup ideas: (1) raises the wages of engineers, (2) raises the retained equity of entrepreneurs, (3) raises expected profits, (4) lowers realized profits, (5) raises the startup probability of success, and (6) has an ambiguous effect on entrepreneurship.

**Proof.** For (1), when $\kappa$ increases, the ratio of engineers to ideas decreases ($a = S/\kappa$), and so it directly follows from Lemma 2 that engineer wages increase. For (2), from Equation 6, it follows that retained equity increases. For (3), expected profits rise since wages raise, i.e., $\frac{\partial w}{\partial \kappa} = \frac{\partial}{\partial \kappa} [q_0 \pi] > 0$. However, for (4), realized profits fall because wages increase. For (5), recall that

$$\frac{\partial w}{\partial a} (1 + d(w)q_0) = \pi \frac{\partial q_0}{\partial a}, \quad (20)$$

which implies that $\frac{\partial w}{\partial a}$ and $\frac{\partial q_0}{\partial a}$ have the same sign. From (1), we know that $\frac{\partial q_0}{\partial a} < 0$, and hence that $\frac{\partial q_0}{\partial a} < 0$. Therefore $\frac{\partial q_0}{\partial a} > 0$, meaning that the startup probability of success increases. For (6), because $w$ goes up, $d(w)$ goes down, but $q_0$ goes up. As such, the effect of a change in the stock of ideas on $q_0 d(w)$ is ambiguous, and hence the effect on entrepreneurship is ambiguous.

What causes shocks in the innovation environment? Clearly publicly funded R&D and academic research is one source of startup ideas. However, it thinking of startup ideas as mapping 1:1 with some kind of basic research insight likely misses the nature of most startup ideas, particularly for software. A stylized history of commercial innovation would highlight firms “working through” what businesses are now feasible in response to the introduction of a general purpose technology. In broad strokes, a new general purpose technology emerges—the railroad, the internal combustion engine, electricity, the transistor, the integrated circuit, the personal computer, the Internet, the smartphone and so on (Jovanovic and Rousseau, 2005). Initially, what is possible, business-wise, is poorly understood, ala Pástor and Veronesi (2009). Startups pursue whatever business ideas now (seemingly) become feasible. The technology matures and the contours of what is possible and profitable become apparent.

6 Product market

A larger product market means each successful firm wants to hire more workers. The prize to the successful entrepreneur has also increased, though these though these larger rewards are attenuated by the higher labor costs (though overall entrepreneurship increases).
Proposition 4. An increase in the size of the product market: (1) raises the wages of engineers, (2) raises the retained equity of entrepreneurs, (3) lowers the startup probability of success, (4) raises expected profits, (5) raises realized profits, and (6) increases the fraction of engineers pursuing entrepreneurship.

Proof. For (1), differentiating the expression for engineer wages by \( R \), we have
\[
\frac{\partial w}{\partial R} = q_0 \phi(L) + \pi \frac{\partial q_0}{\partial R}.
\] (21)
Assume that \( \frac{\partial w}{\partial R} \leq 0 \). Since \( q_0 \phi(L) > 0 \), for the equality to hold, \( \pi \frac{\partial q_0}{\partial R} \leq 0 \), but by Lemma 1, \( \frac{\partial q_0}{\partial R} > 0 \), given the assumption that \( \frac{\partial w}{\partial R} \leq 0 \). Claim (2) follows directly from Equation 6. For (3), because wages rise, \( q_0 \) falls. For (4) expected profits rise, since \( \frac{\partial w}{\partial R} = \frac{\partial}{\partial R} \left[ q_0 \pi \right] \). And for (5), the effect of a larger product market on realized profits is also positive because expected profits rose and yet \( q_0 \) went down. For (6), as both \( q_0 \) and \( d(w) \) go down, \( g \) goes up, meaning a greater fraction of engineers are pursuing entrepreneurship. □

Figure 5 illustrates some of the effects of a positive product market shock. It is useful to think of the effects of the product market shock before engineers adjust occupations. When \( R \) increases by \( \Delta R \), despite each firm wanting to hire more employee-engineers, the number of workers per firm cannot adjust, as \( L^* \) is fixed. As such, \( w \) increases. However, because of the concavity of \( \phi(\cdot) \), profits increase despite this wage increase.\(^\text{10}\) These higher profits draw more workers into entrepreneurship, further increasing wages but also lowering \( L^* \).

The size of product markets served by Silicon Valley change both for technical reasons (e.g., the proliferation of the smartphone) and for non-technical reasons, such as the emergence of new markets (e.g., the rise of China and India). In the language of the model, the proliferation of the smartphone could be thought of as changing both \( \kappa \) and \( R \) simultaneously, while the rise of China might be thought of as just a change in \( R \).

\(^{10}\)In the short-run, \( w(R) = R\phi(L^*) \) and \( w'(R) = \phi'(L^*) \). By the envelope theorem, \( \pi'(R) = \phi(L^*) - w'(R)L^* = \phi(L^*) - L\phi'(L^*) \). Because \( \phi(\cdot) \) is concave, \( \pi'(R) > 0 \).
The recent enormous growth in startup valuations has lead many to see a bubble, ala the 2000 dot com crash. However, it is hard to overstate how much larger product markets are today to Silicon Valley companies. In 2000, the percentage of the global population using the Internet was approximately 7%, and as of 2014, it was 39%. Facebook alone recently passed a milestone with 1 billion users using the service on a single day. Over a shorter time frame, there has been enormous growth in the fraction of users with smartphones and thus in the demand for mobile applications (Ghose and Han, 2014).

### 6.1 The allocation of entrepreneurs over ideas

It is useful to consider how entrepreneurs self-allocate over the available ideas. Consider a small change, \( dE \), in the number of entrepreneurs. This causes the marginal idea to decrease from \( q_0 \) to \( q_0 - dq_0 \). The new marginal, previously unexplored, idea has \( \kappa dq_0 f(q_0) \) entrepreneurs pursuing it. Each idea of success probability \( q \), which previously had \( q/q_0 \) entrepreneurs pursuing it, now has \( q/q_0^2 dq_0 \) additional entrepreneurs. The total increase in engineers pursuing already-covered ideas is thus

\[
\kappa \int_{q_0}^{1} \left( \frac{q}{q_0^2} \right) dq_0 f(q) dq = \frac{dq_0}{q_0} E. \tag{22}
\]

and so \( dE = dq_0 \kappa f(q_0) + \frac{E}{q_0} dq_0 \). The fraction of the marginal entrepreneurs devoted to new idea exploration is thus \( \kappa f(q_0) q_0 E^{-1} \). The exploration return to more entrepreneurs is

\[
\frac{dq_0}{dE} = -\frac{1}{E/q_0 + \kappa f(q_0)}. \tag{23}
\]

Note that if \( f(q_0) = 0 \) (contra our assumption), there is no “idea mass” at \( q_0 \), and \( \frac{dq_0}{dE} = -\frac{q_0}{E} \), which implies that \( \epsilon^q_\text{E} = -1 \), where \( \epsilon^q_\text{E} \) is the elasticity of success probability with respect to the number of entrepreneur-engineers. A unit elasticity implies that a percentage increase in engineers causes an equally sized decrease in the success probability. If \( f(q_0) = 0 \), then there would no longer be a single entrepreneur pursuing \( q_0 \)—there would be a more entrepreneurs "pooled up" at the worst idea, as there is no new idea for a would-be entrepreneur to pursue.

If there is a small change in the number of entrepreneurs, what is the split of those new entrants over entry on already-funded ideas versus exploration of new ideas?

This entry can be me-too biased (a larger fraction of the entrepreneurs pursuing ideas already being pursued by incumbents). From a social standpoint, we want exploration-biased entry into entrepreneurship. If more engineers can be induced to enter entrepreneurship while keeping all else equal, this change is “exploration biased” (more engineers pursuing previously un-pursued ideas) when startup success probability is high and “me too” biased when startup success probability is low (more entrants on ideas already being pursued). From a social perspective, more entrepreneurs have the biggest returns when (a) the startup success probability is high, (b) there are few existing entrepreneurs and (c) the innovation space is thick with “marginal” ideas, in the sense that \( f(q_0) \) is high.

The size of the increase in exploration and the efficiency with which marginal engineers are employed can seem counter-intuitive. For example, there is less of a decrease in the marginal idea when \( \kappa \) is high, simply because there are still lots of good ideas. When \( \kappa \) is high, adding more engineers is more efficient, in the sense that a greater fraction are devoted to exploring new ideas. When \( f(q_0) \) is high, there is less exploration, because it takes a smaller shift down the idea distribution to “absorb” the new engineers. However, again, a high \( f(q_0) \) implies an efficient use of these entrepreneur-engineers.
7  The need for a Silicon Valley theory of entrepreneurship

The very title of this paper implies I believe there is something unique about Silicon Valley entrepreneurship that distinguished it from technological entrepreneurship, nevermind conventional entrepreneurship. One key difference already discussed at length is the special role played by engineers. What I perceive to be the other important differences are manifested in the assumptions I make. The key assumptions are that: (1) selection into entrepreneurship is not driven by risk preferences or differences in productivity in the two “sectors.” (2) unlike markets-for-ideas approaches that emphasize patents or other intellectual property rights protections, ideas are non-rivalrous, free for anyone to pursue and yet still they lead to quasi-rents (3) price-taking occurs in some markets (for capital and engineers) but there is market power in other markets (namely in the product markets).

My assumptions do not universally apply to all forms of technology entrepreneurship. For example, patents clearly and obviously matter in the pharmaceutical industry. But that does not mean patents matter much at all for the kind of software-focused Silicon Valley entrepreneurship this paper is about. These kinds of differences are arguments against trying to fit all this literature into the Procrustean bed of “entrepreneurship.”

7.1 Entrepreneurship as a rational choice

Selection into conventional entrepreneurship is hard to explain, in part because it seems like such a bad deal: in simple hedonic wage regressions, self-employment is associated with substantially lower earnings (Hamilton, 2000). Economists posit that perhaps the value in being ones’ own boss is very large (Hamilton, 2000); others posit systematic over-confidence or hubris (Hayward et al., 2006).

The conventional would-be entrepreneur believes she sees a market inefficiency. For business ideas of the flavor “this strip mall would be a good place for a dry cleaners”, the entrepreneur has to assume that large numbers of people before her have over-looked the opportunity or miscalculated the returns to the proposed venture.11 The economist aversion to “$20 bill on the sidewalk” stories is apparently shared by banks, which have a strong preference for securitized business loans. As such, the intrepid (but under-capitalized) entrepreneur must take on enormous personal financial risk to realize their (probably ruinous) vision. This is why the literature has shown convincingly that increases in personal wealth increase entrepreneurship (Evans and Jovanovic, 1989; Blanchflower and Oswald, 1998; Holtz-Eakin et al., 1994; Hurst and Lusardi, 2004; Lindh and Ohlsson, 1996; Nanda, 2010).

The economic rationale for technology entrepreneurship is fundamentally different from that of conventional entrepreneurship. When a would-be investor asks “why has no one else already tried this?” an excellent answer is “the fundamental research or technology that makes this business possible did not previously exist.” An even better answer is one followed with “and very few people would have the technical background needed to commercialize this idea.” These kinds of ideas, when paired with people with the technical ability to execute on those ideas, can create vast fortunes. This potential is why a specialized venture capital industry emerged, making unsecured funds available to the right kinds of people pursuing the right kinds of business ideas. The availability of unsecured capital largely eliminates the personal downside risk of Silicon Valley entrepreneurship (with the exception of the opportunity cost of foregone wages). Hall and Woodward (2010) finds that although venture-backed entrepreneurship is extraordinarily risky (with the modal return being $0), it offers a higher expected return than employment except for those with very large incomes.

11This example business idea is taken from Lazear (2004).
7.2 Selection into entrepreneurship

I assume both workers and entrepreneurs are risk neutral. This stands in contrast to some models of entrepreneurship where differences in risk preferences determine occupational choice, ala Kihlstrom and Laffont (1979). However, this risk-based view is not the only view of entrepreneurship, with other views characterizing entrepreneurs as those with special ability at seeing opportunities missed by others (Schultz, 1975; Rosen, 1983). Regardless, I am assuming something weaker than risk neutrality, namely that if firms cannot screen workers on their risk preferences, then what matters is that the marginal engineer with respect to occupational choice is risk neutral. Further, if there is a gap between the equilibrium that would arise with risk neutral entrepreneurs and some population of engineers with some distribution of preferences, the risk-adjusted equilibrium would “move” towards what would arise with risk-neutral engineers, making it more likely that the marginal (i.e., indifferent) engineer is de facto risk neutral. In addition to these more theoretical arguments, I will argue risk preferences are relatively less important for Silicon Valley entrepreneurship than conventional entrepreneurship for a host of reasons.

My paper is not the first to highlight the employment versus entrepreneurship dilemma as a utility-maximization problem. Hall and Woodward (2010) determine the returns to founders of a large number of VC-backed technology startups and determine the level of risk aversion, assets and outside employment salary that would make a would-be entrepreneur just indifferent. Although the modal return to entrepreneurship in their data is zero, the expected value from an entrepreneurial venture is $4.4 million.

7.2.1 Only the risk preferences of the marginal engineer matter

Let us suppose, contrary to the model, that engineer risk preferences are important in determining occupational choice. To consider how this changes things, let’s first suppose that if all engineers were risk neutral, the equilibrium fraction of entrepreneurs would just be $g$. Now, assume those engineers have heterogeneous risk preferences, parameterized by $\alpha$, which has a cdf $G$. The relatively more risk averse engineer would choose employment, and the relatively more risk seeking would choose entrepreneurship. Figure 6 plots the subjective utility of employment, and the subjective utility of entrepreneurship versus the risk preference parameter. All parties put the same value on the fixed wage of $w$, but the subjective utility of entrepreneurship is declining with increasing risk aversion. On the plot, I show three potential equilibrium values for $g$ that might arise if engineers were risk neutral, $g_A$, $g_B$ and $g_C$. At $g_A$, the marginal engineer is risk seeking, at $g_B$, risk neutral and at $g_C$, risk averse.

Let $G(\hat{\alpha}) = g$, making $\hat{\alpha}$ the risk parameter of the marginal engineer with respect to occupational choice. The relevant question for assessing how the equilibrium changes when we factor in risk preferences is this: at $\hat{\alpha}$, what is the sign and magnitude of $u(w; \alpha) - q_0 u(e\pi; \hat{\alpha})$?

At $g_A$, the pseudo-marginal engineer (in the sense that they are not actually indifferent at the $g_A$ equilibrium) is risk seeking. Some number of engineers more risk seeking than them will switch to entrepreneurship until returns are equalized. After this adjustment, the truly marginal engineer will have risk preferences closer to neutral. By the same argument, if the equilibrium is such that the pseudo-marginal engineer is risk averse, the risk-adjusted equilibrium will move so that the marginal engineer has preferences closer to neutral. In either case, even if the competitive, “risk neutral” equilibrium is not compatible with the distribution of risk preferences, the equilibrium moves towards an equilibrium where the marginal engineer has a less-curved $u(\cdot)$. As it is the curvature of $u(\cdot)$ that creates tractability problems in analyzing a model, this movement is good news.

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12 Arora and Nandkumar (2011) is another example of research in this “rational” frame.
Figure 6: Risk aversion and the marginal engineer

Notes: This figure illustrates how different equilibria under the assumption of risk neutrality for all engineers leads to the pseudo-marginal engineer to not be indifferent between career options (when engineers do differ in preferences over risk). See Section 7.2.1 for details.

Of course, the risk-adjusted equilibrium could, in principle, be far away from “natural” value of \( g \), and the curvature in \( u(\cdot) \) would matter. However, as risk aversion is much more common than risk seeking, we might imagine that \( G(0 - \epsilon) \approx 0 \), with a substantial amount of weight at \( G(0) \) but with most of the mass to the right. In other words, we would see no risk seeking engineers, a sizable number of risk neutral engineers and then everyone else with some degree of risk aversion. As employment is much more common than entrepreneurship even in Silicon Valley entrepreneurship (see Section 7.3), at plausible values of \( g \), the the marginal engineer, and the engineers to her right and left, is likely to be tolerant of risk and reasonably approximated as risk neutral.

If it is not risk, then perhaps selection into entrepreneurship is driven by productivity differences.\(^{13}\) One could easily imagine a Roy-style model where people have different returns in different sectors, and then a person who gets \( w_A \) in the \( A \) sector cannot just get \( w_B \) in the \( B \) sector (Roy, 1951). But here again, the unique nature of technology entrepreneurship matters. The conventional entrepreneurship literature, particularly Lazear (2004), has emphasized the importance of balanced skills for entrepreneurship—entrepreneurs must be “jacks of all trades.” For technological entrepreneurship, at least one entrepreneur must be a master of at least one trade, namely the technology in question, which is often computer science, electrical engineering, chemical engineering, biochemistry and so on. These engineers are needed to recognize the idea ex ante, build the prototype, hire more engineers,\(^ {14}\) and solve technical challenges. Starting a technology company, at least a first, and working for a technology company are similar. By contrast, opening a restaurant is not similar to being a sous chef or a waiter. An engineer at Google and an engineer co-founder at a three-person startup are doing more or less the same thing, namely writing

\(^{13}\)Some research, such as Levine and Rubinstein (2013) looks at personality differences that could explain selection, finding evidence that traits like intelligence and some history of transgressive behavior are predictive of becoming an entrepreneur.

\(^{14}\)There is often-stated maxim in Silicon Valley that non-technical people cannot evaluate, and thus cannot effectively hire, technical people.
software that will (in the case of Google) or they hope will (in the case of the startup) be used by a large number of people. This is not to say that being an entrepreneur-engineer and an employee-engineer are the same, but rather that these differences are not stark that radically different kinds of people choose one or the other.

7.3 The Careers of Stanford Computer Science PhDs

A key claim of the paper is that both Silicon Valley entrepreneurs and employees are drawn from the same pool of individuals—namely elite engineers. To assess this claim, I constructed a dataset on the careers of PhD graduates from Stanford School of Engineering's Computer Science Department. Although I focus on PhDs, the department publicly lists the names of alumni from each of its three degree programs: Bachelors (2,811 students), Masters (4,410 students) and the PhD (866 students).\footnote{Available at http://cs.stanford.edu/alumni.} Even a cursory inspection of these lists turns up important Silicon Valley participants. For example, the first page of the “Undergraduates” list shows Brian Acton, who (1) worked as engineer for Adobe and Yahoo! for most of his career and (2) founded WhatsApp shortly after being turned down for an engineering job at Facebook and, (3) founded and later sold WhatsApp Facebook for $19 billion. (Perhaps the most famous non-graduates of the program are Larry Page and Sergey Brin, the founders of Google.)

Although I lack data on the decision-making of individual graduates, I can at least look at their realized career paths to see how common entrepreneurship and employment is and whether individuals move back and forth between these options. A research assistant downloaded the LinkedIn profile for every listed PhD graduate. One I had downloaded the profile associated with each individual, I then extracted listed schools, work experiences and skills.\footnote{Extraction was done using the open source tool \texttt{lip2sql} which I commissioned for this project. It is available at https://github.com/johnjosephhorton/lip2sql.} Figure 7 shows the number of Stanford CS graduates per year with LinkedIn profiles.

Of the 866 PhD alumni listed on the website, 423 had publicly available LinkedIn profiles. Those with LinkedIn profiles collectively listed 1,616 post-graduate worker experiences. To identify entrepreneurial

\begin{center}
\begin{figure}
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\includegraphics[width=0.5\textwidth]{figure7}
\caption{Number of Stanford Computer Science PhDs Awarded Per Year with LinkedIn profiles}
\end{figure}
\end{center}

Notes: This plots shows the number of Stanford Computer Science PhDs awarded per year for which LinkedIn profiles could be found.
jobs, I searched their listed job titles for the terms “founder,” “owner,” and “partner.” To identify employment, I search their listed job titles for the terms “engineer”, “developer”, and “programmer.” Of the 1,616 experiences, (1) 373 can be classified as some kind of employee engineering role, (2) 169 as a founder or co-founder role, and (3) 1,074 classified as “Other.” Casual inspection of the “Other” experiences shows many academic positions (e.g. professor, scientist, researcher, etc.), managerial roles in industrial settings (e.g., VP of Product Management, SVP) and some positions in the VC industry.

As of 2015, the fraction of graduates with at least one engineer experience is 53%; the fraction of graduates with at least one founder experience is 34%. About 18% of graduates had both entrepreneurial and engineer employment experiences. For each year, I calculated the fraction of all CS PhDs that graduated in that year or before that had, by that date, worked as an engineer or founder, post-graduation. Figure 8 shows these fractions.

Note that the series is not monotonically increasing, since new graduates join the pool each year. If all graduates were picking a single career path post-graduation and new graduates were choosing careers in the same proportions, then the lines would be flat. Instead, we see a steadily increasing fraction of graduates with both entrepreneurial and engineer employment experience. There is a particularly sharp rise in entrepreneurial experience from 1995 to 2000, going from less 10% to nearly 25%. During that same period, employment experiences also increased, but only about 5% points. What seems probable is that the dotcom boom was pulling more CS PhDs away from academia and that these new entrants were biased towards entrepreneurship.

7.4 The role of ideas

I assume that startup ideas are common knowledge and free for any entrepreneur to pursue with a startup. This “ideas as commons” characterization could be contrasted with the “ideas as property” characterization in which the creator of the commercial idea generates a patentable innovation that they can either pursue themselves or sell to some other commercializing entity. Both characterizations capture some aspect of the reality, though the industry matters: in a survey of high-technology startup entrepreneurs, Graham et al. (2009) find substantial cross-sector differences in the importance of patents, with software companies viewing patents as much less important compared to the biotechnology and
medical device sectors.

An advantage of the “ideas as commons” framework is that it becomes possible to reason directly about the comparative statics when putting more ideas into that commons: the innovation environment is no longer a source of idiosyncratic shocks—“bolts from the blue” pursued by lone geniuses enthralled by wild spirits—but rather a parameter of the model.

In the popular conception of Silicon Valley, a would-be entrepreneur spots “a great idea for a startup”—a multi-million-dollar bill no one else has noticed. This is far cry from how Silicon Valley practitioners themselves talk about ideas. Some claim “ideas don't matter” and asking a potential investor to sign a non-disclosure agreement to hear a startup idea is a shibboleth that reveals the idea-proposer to be an amateur. Coming from VCs, this is perhaps self-serving, and ideas clearly do matter, but the wisdom of the “ideas don't matter” perspective is that: (1) there are lots of ideas “in the air,” and (2) any obviously good idea will attract lots of entrants, so execution is paramount. The VC focus on the probability of successful execution does not seem to be simply cheap talk—Bernstein et al. (2014) shows that potential investors are far more responsive when evaluating pitches to the characteristics of the founding team than any other source of information.

Many of the most significant technology companies of the last 40 years have been more in the “ideas as commons” flavor, even those successes that were built around a clear and distinct technological innovation: Oracle commercializing Codd’s invention of the relational database (Codd, 1970); Microsoft building a Basic interpreter for the Altair home computer and an OS for the IBM PC; Google developing a link-structure-focused search engine and so on (Brin and Page, 1998). In none of these cases was patenting important in explaining their successes. For some more notable recent technology companies—Amazon, Facebook, Twitter, Uber, Airbnb—despite making heavy use of technology, and in some cases pursuing patents, they seem to have nothing essential to their business that is patentable.

One critique of “ideas as commons” is that discovery takes costly, purposeful effort, e.g., (Romer, 1990). This is certainly true, but the goal of this paper is to understand the entrepreneurial commercialization of new ideas, not their origins. It bears repeating that a large portion of software entrepreneurship ideas are of the “this would be a good place for a dry cleaner’s” flavor than “this alloy of silicon and germanium will help us build integrated circuits” flavor. Even when fundamental research is being developed, it is rarely pursued by startups (at least with capital being provided by VCs). The pitch startups make to VCs for capital is about commercializing some existing idea, that the will use that money for basic R&D.

Much of the original idea-generation effort is borne by the public, through publicly funded R&D, much of which is directly and explicitly put in the commons. Even non-publicly funded academic research is often put in the commons (through academic publication) without any attempt to explicitly patent that work. Agrawal and Henderson (2002) finds that in the case of the Mechanical and Electrical Engineering Department at MIT, researchers claimed that less than 10% of the knowledge transferred out of their labs was patented. I suspect that this fraction would be even lower for computer science academia, which has a much stronger culture of open source development and patents are rare.

Even when not put in the commons, an emerging literature finds evidence of substantial R&D spillovers, e.g., Moretti et al. (2014); Azoulay et al. (2014), with this government R&D causing more R&D spending by nearby industrial labs. While this does not make the case that ideas are in common, it is highly suggestive that technological innovation does not stay hermetically sealed within the confines of the originator’s lab, regardless of lab type, but rather seems to get “in the air” and serve as complements to other research programs, with the ideas probably spreading by workers who do not take their non-disclosure agreements too seriously and like to talk about their work.
7.5 Price taking in wages and equity

In the model, VCs, entrepreneurs and engineers are price takers. While price-taking is not always reasonable for labor markets, it seems very likely to hold in the labor markets for engineers. In the actual Silicon Valley, employment is at will, unions are non-existent, non-compete clauses are unenforceable, the market is thick with workers and employers and job hopping is commonplace.\(^{17}\) The on-going litigation against several tech companies for wage fixing is literally the exception that proves the rule: companies fiercely compete with each other for engineers, with wages and equity being a primary recruitment tool.

Although there are fewer VC firms than there are workers, the market is still thick: it is relatively easy for would-be entrepreneurs to “shop around” terms from VCs: a would-be entrepreneur in Palo Alto walking along Sand Hill Road could meet with half a dozen VC firms in an afternoon. Startups have a strong incentive to shop around their term sheets, just as engineers have an incentive to compare job offers.

In the model, VC firms are an undifferentiated mass of “dumb money.” In practice, some firms are better connected, have smarter and more insightful partners and so on. Relying on a dataset of firms receiving multiple term-sheet offers from VCs, Hsu (2004) finds that startups offer a substantial discount to “brand-name” VCs. Although one could imagine thinking about the market as a oligopolistic high end, where one or two VC firms become monopsonists in startup equity, an alternative interpretation is that different VCs offer different compensating differentials, and that entrepreneurs “pay” for these with lower valuations.

8 Conclusion

To the extent this paper offers a “recipe” for creating a “Silicon X”—a common interest among regions looking to create a tech-focused regional hub—it suggests the following: create an environment where (1) lots of ideas will be in the air, (2) lots of engineers will be around to pursue those ideas, and (3) plentiful seed capital will be available to those entrepreneur-engineers. A major research university helps on several dimensions at once, by throwing off ideas and attracting engineers.

Governments can also try to lower startup costs, as some startup costs are affected by government policy. However, not all costs are equally elastic with respect to government efforts. For example, governments can try to lower the cost of capital by setting up tech incubators and providing grants. Given how freely capital flows and the lack of government expertise in picking winners, this seems relatively ill-advised. A better approach might be to focus on reducing costs where government power is at its zenith, such as land use regulation and employment law. Laws can be tilted to make it easier for workers to move between employers (reducing the the enforceability of non-compete and non-solicitation contracts seems promising) and minimize the downside risks of startup failure.\(^{18}\)

At the national level, government policy affects many of the exogenous parameters of the model. From subsidizing STEM education and setting high-skilled quotas, governments can affect the supply

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\(^{17}\)Perhaps unique in the US, billboards along Highway 101 are often “Help Wanted” signs for engineers. The proliferation of company review sites such as Glassdoor—may contain precise wage information per job title within a company—makes it easy for workers to learn the market rates. One source of uncertainty is the large share of compensation that is often offered in equity, but the emergence of secondary markets in stock options of closely held corporations makes it fairly easy for would-be employees to determine the total offered compensation; and if VC investment occurred relatively recently, they can get a strong signal of the market value of any stock options.

\(^{18}\)The supposed Silicon Valley embrace of failure—or least non-stigmatization of it—is cited as cause of its strength. It is at least possible that this view gets the causality wrong—the Silicon Valley equilibrium failure is so common and very common things can’t have a strong stigma.
of engineers in the short and long runs. Regulation about who is allowed to make equity investments surely affects the supply of capital. The importance of policy is perhaps greatest when considering the innovation environment, both through direct subsidization of the R&D (Jaffe, 1989) and their policies on intellectual property.

An additional national “lever” is the supply of engineers, which can be affected greatly by visa policy around high skill immigration. Adding more immigrants imports both supply and demand, so the negative effects on wages might be quite modest. If there is a desire to increase the supply of labor without reducing employee wages, the model suggests an answer: increase R&D spending, as this is likely to increase the stock of ideas, which will have a countervailing effect on engineer wages.

References


