The Impact of Innovation: Does Venture Capital Funding Stimulate Increases in Social Mobility?

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Abstract

Innovation appears to have a direct impact on broad measures of social mobility. The mechanism thought to be behind this is Joseph Schumpeter's theory of creative destruction, where new entrant firms develop more sophisticated technologies in an incessant process of industrial turnover. Thus, the gains in social mobility are dependent on the success of new entrant firms. We hypothesize that in regions with dense concentrations of venture capital funding, new entrant firms will be more successful, and this will amplify the effect that innovation has on mobility. This study contributes meaningful nuance to the argument that innovation causes increases in mobility by showing that the effect may vary in magnitude depending on influencing factors such as venture investment.

Introduction

Technological innovation is arguably the primary factor driving our development as the human species. We started with basic inventions like stone tools, fire, and agriculture that enabled us to thrive in prehistoric environments. Then, we graduated to inventions such as writing, gun powder, and the printing press that propelled us toward civilization and away from our more primitive past. Later, the creation of the steam engine pushes humanity into the industrial age—forever changing our relationship with transportation and manufacturing while thrusting us into an era of unprecedented globalization. Our best estimates tell us that it took about 10,000 years to progress from the advent of agriculture to the steam engine in the late eighteenth century. Moreover, if we use fire instead of agriculture as our starting point, this progression could have taken as long as 1.5 million years. In other words, innovation was a slow, arduous process for most of our human history. But, in the past 300 years alone, we have invented the telegraph, airplanes and automobiles, space flight, cell phones, and the internet—just to name a few. Additionally, in just the past 30 years, we have invented machine learning, cloud computing, and preliminary forms of both artificial intelligence and human genetic modification. Thus, the process behind meaningful innovation is accelerating; the frequency at which our lives are transformed due to new technology is increasing.

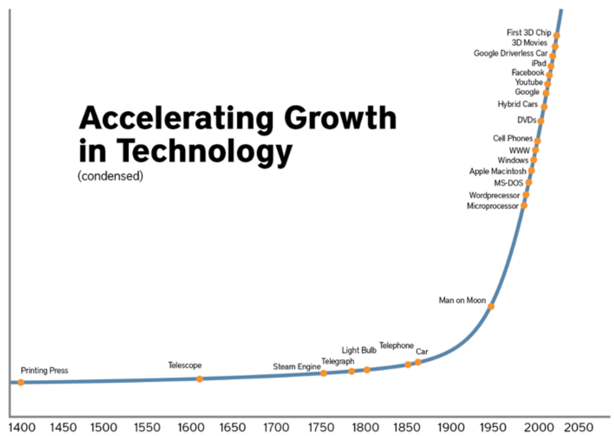

Figure 1: Technological innovation over time

Therefore, it is critical to understand the different ways, both positive and negative, in which this innovation affects our society. One such positive effect can be found in social mobility. Joseph Schumpeter's theory of creative destruction tells us that the incessant process of new technologies overtaking old technologies inevitably leads to higher levels of social mobility. This was empirically confirmed by Philippe Aghion and others at Harvard in their 2016 paper titled "Innovation and Top-Income Inequality". Simply put, this paper is aiming to replicate this result and then test what role venture capital funding plays in this. The hypothesis is as follows: if new entrant innovation is one of the key factors influencing social mobility, then this innovation will have a stronger impact on mobility in regions with high concentrations of venture investment. The reason being that venture capital funding fuels the ecosystem for new entrant innovation. In other words, in regions with high levels of venture investment, new entrant firms have more resources at their disposal when attempting to overtake incumbents, which we are postulating will lead to better outcomes for the new entrants. Put plainly, one unit of innovation might carry more weight in these regions. Following the Schumpeterian model, this should cause a greater impact from innovation on mobility. The data we are using to test this comes from a variety of sources. We source the cross-U.S. commuting-zone data on innovation and social mobility from Aghion et al. (2018). The innovation data in Aghion et al. (2018) comes directly from the USPTO database and the measures of social mobility from Chetty et al. (2014). The data on venture capital comes from a private report from Martin Prosperity Institute. Under one of our model specifications, the findings indicate that the presence of venture capital funding positively influences the effect of innovation on mobility—this is in line with our hypothesis. However, this result is not robust to our alternative specifications. Because the result is not robust across specifications, we are hesitant to draw any conclusions about the significance of the effect.

Literature Review

There is a dense literature on innovation and its effects. However, there is not much research done on the more specific case of innovation's effect on social mobility. The first contribution to the literature that we will discuss is from the twentieth-century Austrian economist named Joseph Schumpeter. Schumpeter's greatest contribution to economics and the one that is most relevant to this paper is his concept of creative destruction. The context in which Schumpeter describes creative destruction remains controversial, but as a standalone idea, it has largely withstood the test of time. He describes it as "the process of industrial mutation that continuously revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one". Following this, a Schumpeterian growth model predicts that innovation (especially new entrant innovation) will lead to both higher levels of income inequality at the top of the income distribution, and higher levels of social mobility throughout. The rationale behind this is that every new technological innovation will increase the innovator's advantage over his competition, allowing the innovator to reduce their demand for labor while increasing their income share at the expense of the worker. This is what causes the growth in top income inequality. Simultaneously, more innovation leads to more creative destruction, which enables new entrant firms to overtake incumbents, fostering greater social mobility. The Schumpeterian growth model that predicts these effects is described mathematically in Aghion et al. (2018), which we will discuss further in later sections. It is also important to note that the effect of innovation on both inequality and social mobility can vary quite significantly depending on a host of factors including information technology, taxes, and policies related to innovation blocking (Jones, Kim 2018). Our research is attempting to add venture capital funding to this short list of factors that affect the impact innovation has on mobility.

Aghion et al. (2018) explores some of Schumpeter's ideas empirically. While their primary analysis is in relation to how innovation impacts societal inequality, there is a section in the paper which discusses the impact on mobility. This analysis is conducted at the US-commuting zone level—there are 741 commuting zones in the US at the time this data was collected. The variables of focus include the metrics used for innovation, mobility, and the set of controls. Innovation is measured via annual new patents per capita granted by the USPTO to new entrant firms, averaged over the period 1998 to 2012. Alternatively, innovation is measured by the number of times these patents were cited in the five years following their finalization—this is also per capita and averaged over the same time period. This second measure of innovation captures not only the raw number of new patents occurring in the region, but also the relative significance of these patents, since more significant patents should be cited for frequently. The authors use a few different measures for mobility, with the primary one being absolute upward mobility. This is defined as the expected percentile (from 0 to 100) for a child whose parents belonged to some P percentile of the income distribution. The percentiles are measured over the period 2011–12 when the child is roughly 30 years old, while the percentile P of the parent's income is calculated over the period 1996–2000, when the child was about fifteen years old. By regressing absolute mobility on innovation plus a vector of controls (including GDP per capita, tax rate, labor force participation rate, etc.), they find that new entrant innovation has a positive and significant effect on social mobility, whereas incumbent innovation does not; this is completely in line with the Schumpeterian growth model described earlier. Thus, we assume from this that new entrant innovation is associated with an uptick in social mobility. However, there is also evidence that incumbent innovation contributes more to overall economic growth than new entrant innovation (Garcia-Marcia, Hsieh 2019). At first, this seems a bit contradictory; however, I don't believe it is. Growth and social mobility are two distinct concepts, and they shouldn't be used synonymously. Thus, it is feasible that, when compared to incumbent innovation, new entrant innovation contributes more to social mobility increases and less to growth.

Meanwhile, we know that venture capital funding only plays a small role in the financing of new patents (Haussler, 2009). However, evidence does show that venture capital funding has a positive effect on innovation at the industry level (Lerner, 2003). This can be attributed to financial security, monitoring, and advising that venture capital firms provide to their portfolio companies. As stated before, we are hypothesizing that innovation will have a stronger impact on mobility in regions with high concentrations of venture investment. The mechanism here would be that new entrants overtake incumbents more easily in such regions due to the support they get from venture capital firms. The crucial assumption that we make here is that venture capital investment is beneficial to the new entrant firms in the first place. We have not found any research that confirms this, perhaps because it is so intuitive. By its very nature, venture investment supports start-ups with high growth potential. We believe it is a fair assumption that this investment is beneficial to the start-ups; if it weren't, we're inclined to think they wouldn't seek it out in the first place. Perhaps the most important background information for venture capital is related to its concentration in certain US cities. According to research from the Martin Prosperity Institute, 82% of US venture investment in 2012 was concentrated in 20 US metropolitan areas. Unlike many other forms of financial investment, venture capital funding is unique in that it is clustered in a few US regions and absent in most other regions (Fritsch, Schilder, 2011). Defining characteristics of these regions generally include having a large technology sector, high levels of urbanization, and high population growth rates. Because venture capital funding is so densely concentrated in such few areas, it is one of the defining traits of the regions where it is prominent.

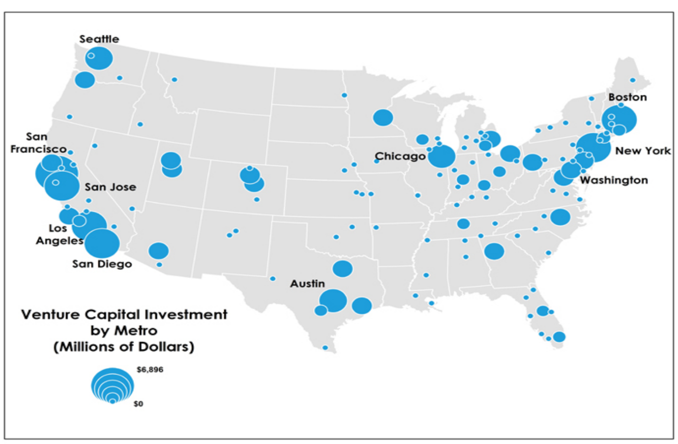

Figure 2: This report comes from MPI's Zara Matheson

There are still plenty of unanswered questions in this realm. To start, aside from Aghion et al. (2018), there is not much research on the causal effects of innovation on social mobility. Also, it is unclear if different types of innovation affect social mobility in differing magnitudes. For example, we do know that new entrant innovation is more significant than incumbent innovation in this sense (Aghion et al. 2018), yet we don't know how region, industry, or economic conditions at the time of innovation might alter our effect on social mobility. Moreover, there are a plethora of unanswered questions in the world of venture capital research. First and foremost, we don't have a great understanding of how venture capital funding affects any measures of macroeconomic activity other than patent counts. Endogeneity is an undeniable factor in the shortage of research here. Establishing any sort of causality between venture capital funding and a measure of economic activity is a tall task.

Theory

The main theoretical idea that we will need is the Schumpeterian growth model from (Aghion et al. 2018). The model begins with a basic, discreet time economy populated by workers and entrepreneurs. For a complete mathematical description of the model, see Aghion et al. (2018). In their paper, they define production, cost, and profit functions, so that they can eventually solve the model for both new entrant innovation and incumbent innovation. Below is the flow chart from Aghion et al. (2018) describing the innovation process in the context of their model.

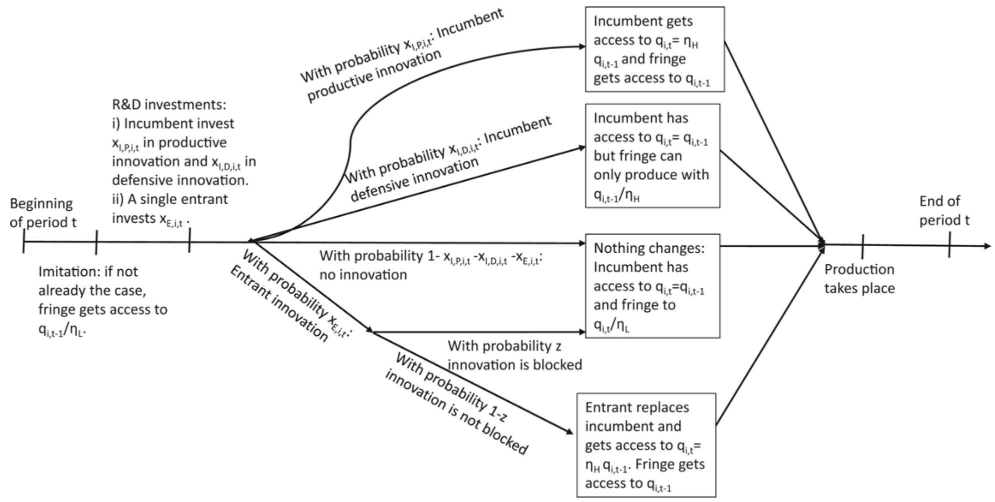

Figure 3: For a clearer understanding of the mathematical notation used, see the original paper. For our focus, we care about how social mobility is impacted by this process. Similarly, we are interested in the lower path for new entrant innovation and how it is affected by z.

For the purposes of this paper, we only need to consider one equation from their model, which is the social mobility term:

$$\Psi_t = \chi_{Et}(1 - z) / L, \tag{1}$$

where χ_{Et} is intensity of new entrant innovation, $L \geq 1$ is the ratio of workers to entrepreneurs, and z is the probability that an incumbent firm successfully blocks a new entrant firm. In the context of our analysis, z might be instead thought of as the probability that the new entrant is unsuccessful in its efforts to develop to the point where it is able to overtake the incumbent. The reason for this might often be due to lobbying, but we believe it is more frequently due to reasons such as lack of funding, poor decision making, and other operational issues.

To reiterate, at the level of the individual firm, our hypothesis is that access to venture capital funding will increase the probability that innovation by a new entrant firm develops to the point at which the new entrant is able to overtake the incumbent; the primary reason being that venture capital firms provide crucial financial security, monitoring, and advising to new entrant firms. In the context of this model, this would suggest that increasing venture capital funding decreases our z value. Under this hypothesis, increasing venture capital funding, and thus decreasing z, should result in new entrant innovation having a stronger effect on mobility all else equal. In aggregate, the interpretation is slightly different: in aggregate, this would imply that innovation has a greater impact on mobility in regions with high amounts of venture capital funding. This is what we will be testing empirically.

Empirical Strategy

In order to test this hypothesis empirically, we use a strategy very similar to that in Aghion et al. (2018). In order to describe our empirical approach, let us first define variables for venture capital funding, social mobility, innovation, and a set of controls that include population growth rate, tax rate, labor participation rate, log of GDP per capita, government size, public-school expenditure per student, and whether the commuting zone can be described as urban.

I. Venture Capital

Venture capital funding is defined as the per capita venture capital investment amount in US dollars for the year 2012. We use this value as a dummy variable. Due to some constraints in the venture capital data set (which are described at length in the Data section), we code this dummy variable as a 1 for the top 45 commuting zones by venture investment and a 0 for the remaining commuting zones. The reason this is applicable is because by the time one reaches the 45th highest commuting zone by venture investment, the per capita values come all the way down to

$37 from the high of $2,103. Thus, any commuting zones below this must have a value between $0 and $37. Given what we know about the uneven distribution of venture capital, in all likelihood, the true value for the vast majority of these remaining commuting zones is $0 or close to $0. However, this sort of binary grouping does open the door to endogeneity. Despite our claim that high venture investment is one of the defining features of these top 45 commuting zones, there is the possibility that by doing this grouping, we are attributing the effect of omitted covariates to venture capital funding. In order to combat this, we control for factors that might otherwise be attributed to this binary venture capital variable. Examples of these controls include GDP, size of the finance and manufacturing sectors, and population growth rate. Additionally, we run a second regression where the venture capital data is kept in continuous form, with imputed values for each of the commuting zones outside of the top 45. We impute an annual per capita value $0 for each of these zones—this follows our assumption that there is little to no venture capital funding outside of the top 45 commuting zones.

II. Social Mobility

For our measure of social mobility, we use the absolute mobility metric described previously. In our case, this is defined as the expected percentile (from 0 to 100) for a child whose parents belonged to the 25th percentile of the income distribution. The percentiles are measured over the period 2011–12 when the child is roughly 30 years old, while the percentile of the parent's income is calculated over the period 1996–2000, when the child was about fifteen years old. Separately, we use a similar measure that is defined as the probability of a child to belong to the 5th quintile of income distribution at age 30 if their parent belonged to the 1st quintile. This is measured over the same period as the absolute mobility measure.

III. Innovation

Our innovation variable is defined exactly the same as in Aghion et al. (2018). To reiterate, innovation is first defined as annual new patents per capita granted by the USPTO, averaged over the period 1998 to 2012. Alternatively, this value is weighted by the number of times these patents were cited in the five years following their finalization—this is also per capita and averaged over the same time period. We will move forward with this second measure, for it considers the usefulness of the patent: more useful patents are more frequently cited. This second measure can also be separated into the case where the patents come from new entrant firms, and the case where they come from incumbent firms.

IV. Controls

We use a set of control variables that include population growth rate, log of GDP per capita, public school expenditure per student, local average tax rate, labor force participation rate, size of finance sector, size of manufacturing sector, size of government sector, and whether or not the region can be thought of as urban as opposed to rural.

As a reminder, we wish to test whether or not new entrant innovation has a stronger effect on mobility in regions with higher amounts of venture capital funding. In order to do this, we will first regress social mobility on new entrant innovation, incumbent innovation, and our set of controls. The purpose of this is to validate the assumption we derive from the Schumpeterian growth model that new entrant innovation has a significant effect on mobility whereas incumbent innovation does not. This finding is foundational to our analysis. Our cross-sectional multivariate regression equation is:

$$y_k = \beta_0 + \beta_1 innov_{NEk} + \beta_2 innov_{ICk} + \beta_3 finance_k + \beta_4 manufacturing_k + \beta_5 urban_k + \beta_6 popgrowth_k + \beta_7 tax_k + \beta_8 laborforceparticpation_k + \beta_9 GDP_k + \beta_{10} government_k + \beta_{11} schoolexpenditure_k + \varepsilon_k, \tag{2}$$

where the dependent variable is our mobility measure, $innov_{NEk}$ is new entrant innovation, $innov_{ICk}$ is incumbent innovation for commuting zone k. We use robust standard errors.

To validate our hypothesis—and to replicate the findings in Aghion et al. (2018)—we would like to find a positive and significant value for β_1 and an insignificant (or significant and small) value for β_2. Following this, we will remove the incumbent innovation term and continue with new entrant innovation as our sole measure for innovation since the effect of new entrant innovation is our primary focus. Then, we add our venture capital variable to the model both as an individual covariate and in an interaction term with innovation. The equation becomes:

$$y_k = \beta_0 + \beta_1 innov_k + \beta_2 finance_k + \beta_3 manufacturing_k + \beta_4 urban_k + \beta_5 popgrowth_k + \beta_6 tax_k + \beta_7 laborforceparticpation_k + \beta_8 GDP_k + \beta_9 government_k + \beta_{10} schoolexpenditure_k + \beta_{11} venturecapital_k + \beta_{12}(venturecapital_k * innov_k) + \varepsilon_k, \tag{3}$$

where $venturecapital_k$ is our measure of venture capital funding in commuting zone k.

This is really the model of focus. In order to see how our results vary with different model specifications, we will run the regressions separately with both of our measures of mobility and two versions of the venture capital data (binary and continuous). The results that would confirm our hypothesis are ones in which the β_{12} term is positive and significant at the 5% level. This would support the hypothesis that innovation has a stronger effect on social mobility in regions with higher venture capital funding. There are a multitude of ways the results could contradict our hypothesis. Namely, the β_{12} term could be negative or insignificant, the coefficient on innovation in (2) could be negative or insignificant, or the result could fail to remain consistent across model specifications.

Data

My data can be separated into four distinct categories: social mobility, innovation, controls, and venture capital funding. The first three come from Aghion et al. (2018), while the venture capital data comes from a 2013 report by the Martin Prosperity Institute.

I. Social Mobility Data

The data on social mobility comes from Aghion et al. (2018), yet it originates from Chetty et al. (2014). By using granular historical income data, Chetty et al. (2014) was able to compute various measures of intergenerational mobility for commuting zones across the US. As was stated earlier, we consider two measures for social mobility in our analysis. The first being absolute mobility—which we define earlier as the expected percentile (from 0 to 100) for a child whose parents belonged to the 25^{th} percentile of the income distribution —and the second being the probability of transition from the 1^{st} quintile of the income distribution to the 5^{th} quintile over the course of one familial generation. We observe from this data that intergenerational mobility varies significantly across US commuting zones. For example, the probability of transition from the 1st quintile of the income distribution to the 5th quintile is as low as 2.2% in Greenville, Mississippi and as high as 35.71% in Lemmon City, South Dakota.

Table 1: Social mobility data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
abs_mob	667	43.834	5.478	33.139	39.794	46.706	64.019
pq5q1	675	9.708	4.811	2.210	6.548	11.565	35.714

II. Innovation Data

The data for innovation also comes from Aghion et al. (2018) yet originates from the USPTO. As stated before, innovation is defined as the annual number of new patents granted by the USPTO per capita. This value is weighted by how frequently the patent was cited in the five years following its application date and then averaged over the years 1998 to 2012. Because of a lag between application and grant, the data in years 2007 or later suffers from truncation bias. However, this is corrected for using the distribution of time lags between the application and granting dates and extrapolating the number of patents by states following Hall et al. (2001). At first, this patent data is collected at the state level; the state is found by associating patents with the state of their primary inventor, and the year being the year when the application is deemed complete by the USPTO. In order to get this data to be compatible with commuting-zone-level mobility data, it is converted to the commuting zone level using the county of the patent's inventor. We can see from the table below that the vast majority of total innovation is coming from incumbents as opposed to new entrants.

Table 2: Innovation data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
innovation_total	677	351.278	1,676.302	0.000	3.246	74.694	28,586.990
innovation_incumbent	677	259.991	1,247.708	0.000	1.264	50.990	21,662.880
innovation_entrant	677	38.556	197.686	0.000	0.460	10.162	3,092.687

III. Venture Capital Data

Finally, the venture capital data comes from a 2013 report by the Martin Prosperity Institute. The data describes venture investment per capita for the top 20 US metropolitan statistical areas (MSAs) in US dollars. However, we must have our data at the commuting zone level in order to carry out our analysis. Thus, the venture capital data (which covers the year 2012) is converted from MSAs to commuting zones using a methodology from the US Department of Agriculture. In general, MSAs encompass one or more commuting zones. In fact, for eleven of our original 20 MSAs, the MSA maps perfectly onto exactly one commuting zone. The remaining MSAs cover two or more commuting zones. In these cases, we assume the MSA has an even distribution of venture capital investment across each of the associated commuting zones. We then find the associated per capita value using the population of each commuting zone. This introduces some sample bias; in all reality, the true proportions of venture capital funding would not be equal across the commuting zones that make up an MSA. Nevertheless, this is a natural consequence of the limited supply of data on venture capital and we must carry on with this bias in mind. After the conversion, we are left with 45 commuting zones with positive values. Following our rationale in the Empirical Methods section, we assume that the vast majority of the commuting zones outside of the top 45 will have values at or close to zero. Below are summary statistics for the data in both continuous and dummy form.

Table 3: Venture capital data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
VC	677	13.556	109.824	0	0	0	2,104
VC_binary	677	0.065	0.247	0	0	0	1

IV. Control Data

The data for the controls all comes from Aghion et al. (2018). Local tax rate is the average tax rate in the commuting zone, school expenditure per student is average public school expenditure per student in grades 12 and below in log form, labor force participation rate is average labor force participation rate in the commuting zone, manufacturing employment share is the share of employed persons 16 and older working in manufacturing, population growth is the average population growth rate, log of GDP is the log of GDP per capita, government size is the share of GDP accounted for by the government sector, and finance size is the share of GDP accounted for by the finance sector divided by the same share at the county level. Below are summary statistics.

Table 4: Control data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
localtaxrate	677	22.891	9.322	8	17	26	82
schoolexpenditureperstudent	673	5.982	1.144	3.920	5.145	6.553	11.906
laborforceparticipationrate	677	0.617	0.058	0.364	0.583	0.654	0.782
manufacturingemploymentshare	677	0.148	0.081	0.014	0.085	0.202	0.437
popgrowth	676	0.005	0.010	−0.022	−0.001	0.011	0.044
gvt	676	1.252	0.448	0.000	0.977	1.454	4.429
finance	676	0.775	0.289	0.000	0.585	0.895	2.119
lgdppc	676	3.304	0.183	2.828	3.180	3.393	4.414

Results

I. Regression with New Entrant and Incumbent Innovation

We will start with the regression results from our model in (2). The purpose of this regression is to replicate the finding in Aghion et al. (2018) that new entrant innovation has a significant effect on mobility whereas incumbent innovation does not.

Table 1: Horse Race Regression without VC

	Dependent variable:	
	Probability of 5th to 1st	Absolute Mobility
	(1)	(2)
Entrant Innovation	0.002***	0.003***
	(0.0005)	(0.001)
Incumbent Innovation	0.0001	−0.00004
	(0.0001)	(0.0001)
Finance Industry	0.025	0.977**
	(0.319)	(0.418)
Manufacturing Industry	−14.451***	−16.172***
	(1.825)	(2.393)
Urban	−2.194***	−2.734***
	(0.363)	(0.476)
Population Growth	−24.536**	−52.783***
	(11.528)	(15.119)
Tax rate	−0.021	−0.024
	(0.018)	(0.024)
Labor Force Participation	12.935***	21.400***
	(2.498)	(3.276)
GDP	−3.258***	−7.344***
	(0.926)	(1.215)
Government Size	0.926**	0.252
	(0.471)	(0.619)
School Expenditure Per Student	0.481***	0.743***
	(0.108)	(0.142)
Constant	11.078***	52.658***
	(3.000)	(3.936)
Observations	670	662
R^2	0.313	0.267
Adjusted R^2	0.301	0.255
Residual Std. Error	1,426.792 (df = 658)	1,870.574 (df = 650)
F Statistic	27.237*** (df = 11; 658)	21.571*** (df = 11; 650)

Note: *p<0.1; **p<0.05; ***p<0.01

As we can see in the regression table, new entrant innovation has a significant and positive coefficient when we use both absolute mobility as our dependent variable and when we use the probability of moving from the 1st to 5th quintile over one familial generation as our dependent variable. These are both significant at the 5% level. Meanwhile, incumbent innovation has no significant effect in either case, which is right in line with the predictions from the Schumpeterian growth model. These values are not in logs, so the interpretation in the absolute mobility case is as follows: if we increase the average amount of annual new entrant patent citations in some commuting zone by one, we can reasonably expect to see an increase of 0.003 in the expected percentile (from 0 to 100) for a child whose parents belonged to the 25th percentile of the income distribution. Since one additional patent is such a small, incremental increase, it seems useful to scale this up for comprehension. Since the regression is linear in the coefficients, we can say that for an increase of 1000 in the average amount of annual new entrant patent citations in some commuting zone, we expect to see a 3 unit increase in the expected percentile (from 0 to 100) for a child whose parents belonged to the 25th percentile of the income distribution. The interpretation for our other dependent variable is slightly different: for an increase of 1000 in the average amount of annual new entrant patent citations in some commuting zone, we expect a 2% increase in the probability that a child who grew up in the 1st quintile of the income distribution moves into to 5th quintile by age 30.

II. Regression with Only New Entrant Innovation

We then run the same regression, but this time instead of using both types of innovation, we limit ourselves to new entrant innovation alone. As is evident in the regression table below, the coefficient on our new entrant innovation variable remains the same in this case. This strengthens our claim that, in terms of its effect on mobility, new entrant innovation is more important than incumbent innovation.

Table 1: Regression Using Only Entrant Innovation

	Dependent variable:	
	Probability of 5th to 1st	Absolute Mobility
	(1)	(2)
Entrant Innovation	0.002***	0.003***
	(0.0002)	(0.0003)
Finance Industry	0.015	0.982**
	(0.319)	(0.418)
Manufacturing Industry	−13.911***	−16.442***
	(1.747)	(2.289)
Urban	−2.199***	−2.732***
	(0.363)	(0.476)
Population Growth	−23.364**	−53.372***
	(11.471)	(15.034)
Tax rate	−0.019	−0.025
	(0.018)	(0.024)
Labor Force Participation	12.977***	21.379***
	(2.498)	(3.274)
GDP	−3.129***	−7.409***
	(0.917)	(1.203)
Government Size	0.925**	0.252
	(0.471)	(0.618)
School Expenditure Per Student	0.486***	0.740***
	(0.108)	(0.141)
Constant	10.482***	52.957***
	(2.943)	(3.858)
Observations	670	662
R^2	0.312	0.267
Adjusted R^2	0.301	0.256
Residual Std. Error	1,426.841 (df = 659)	1,869.356 (df = 651)
F Statistic	29.854*** (df = 10; 659)	23.743*** (df = 10; 651)
Note:		*p<0.1; **p<0.05; ***p<0.01

III. Regressions with Venture Capital Dummy Variable Included

Next, we add the dummy variable for venture capital to the model. To reiterate, doing this will help illustrate how the effect of innovation on mobility is different in commuting zones that are in large part defined by their concentrations of venture capital investment—this is the effect that most directly answers my original hypothesis.

Table 1: Regression with Binary VC

	Dependent variable:	
	Probability of 5th to 1st	Absolute Mobility
	(1)	(2)
Entrant Innovation	−0.0003	0.001
	(0.001)	(0.001)
Finance Industry	−0.096	0.913**
	(0.320)	(0.421)
Manufacturing Industry	−12.986***	−15.889***
	(1.770)	(2.331)
Urban	−2.175***	−2.720***
	(0.361)	(0.476)
Population Growth	−18.711	−51.018***
	(11.623)	(15.307)
Tax rate	−0.012	−0.022
	(0.018)	(0.024)
Labor Force Participation	13.303***	21.606***
	(2.489)	(3.277)
GDP	−2.630***	−7.152***
	(0.941)	(1.240)
Government Size	0.933**	0.274
	(0.470)	(0.620)
School Expenditure Per Student	0.503***	0.746***
	(0.108)	(0.143)
Venture Capital	−0.011	0.128
	(0.318)	(0.419)
Interaction of VC with Innovation	0.002**	0.001
	(0.001)	(0.001)
Constant	8.340***	51.824***
	(3.073)	(4.048)
Observations	670	662
R^2	0.321	0.270
Adjusted R^2	0.308	0.256
Residual Std. Error	1,419.902 (df = 657)	1,869.193 (df = 649)
F Statistic	25.827*** (df = 12; 657)	19.966*** (df = 12; 649)
Note:		*p<0.1; **p<0.05; ***p<0.01

The interpretation here feels a bit more difficult. We see that the interaction term between venture capital and innovation is positive and significant for one of our dependent variables and positive yet insignificant for the other. Meanwhile, after including the interaction term, we observe that the new entrant innovation coefficient by itself is no longer significant. Since our venture capital term is serving as a grouping mechanism (grouping high venture capital commuting zones versus low ones), our interpretation is as follows: in areas defined by their large concentrations of venture capital funding (when our venture capital variable codes as a 1), we observe a positive and significant effect from innovation on one out of our two model specifications. In the case where the effect is statistically significant, we interpret this more specifically as: in a high venture capital commuting zone, for an increase of 1000 in the average amount of annual new entrant patent citations, we expect a 2% increase in the probability of a child who grew up in the 1st quintile of the income distribution to move into to 5th quintile. In low venture capital commuting zones, we do not find a significant effect in either direction. We can also consider the relative size of the coefficients from this model when everything is taken in log form.

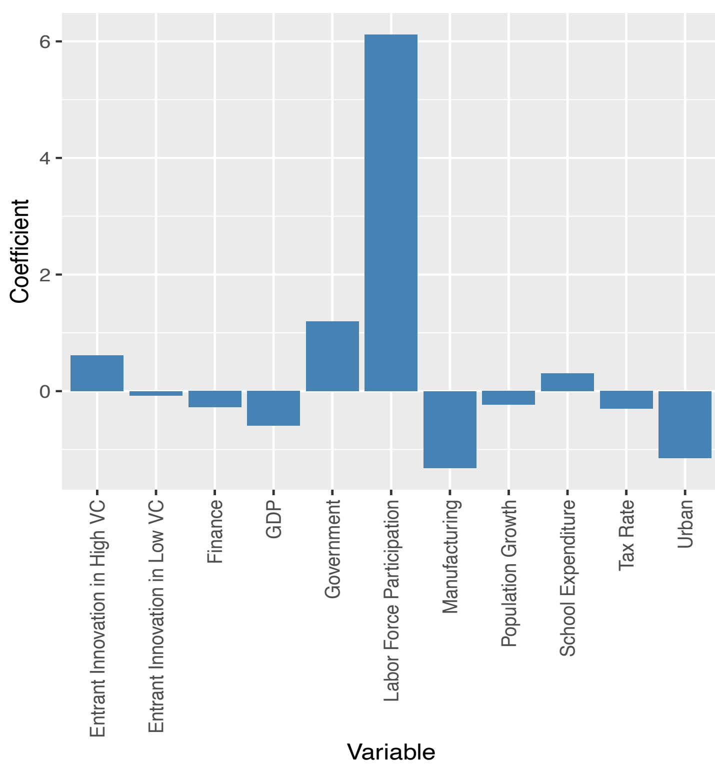

Figure 4: Relative size of coefficients in log form

IV. Regression with Continuous VC Variable

In this regression, we use a continuous version of the venture capital variable as a robustness check. The continuous-by-continuous interaction between innovation and venture capital might be interpreted as a measure of how the effect of innovation on mobility changes as we move our venture capital variable up or down. In order to support our original hypothesis, we would like to see a positive and significant coefficient on this interaction term.

Table 1: Regression with Continuous VC

	Dependent variable:	
	Probability of 5th to 1st	Absolute Mobility
	(1)	(2)
Entrant Innovation	0.002***	0.002***
	(0.0003)	(0.0003)
Finance Industry	−0.291	0.776*
	(0.322)	(0.426)
Manufacturing Industry	−13.233***	−15.674***
	(1.742)	(2.306)
Urban	−2.084***	−2.675***
	(0.359)	(0.476)
Population Growth	−19.115*	−50.922***
	(11.359)	(15.039)
Tax rate	0.001	−0.012
	(0.018)	(0.024)
Labor Force Participation	11.701***	20.540***
	(2.481)	(3.284)
GDP	−3.776***	−7.873***
	(0.917)	(1.214)
Government Size	0.687	0.100
	(0.468)	(0.620)
School Expenditure Per Student	0.511***	0.744***
	(0.107)	(0.141)
Venture Capital	0.005***	0.005**
	(0.001)	(0.002)
Interaction of VC with Innovation	−0.00000***	−0.00000**
	(0.00000)	(0.00000)
Constant	13.156***	54.855***
	(2.965)	(3.927)
Observations	670	662
R^2	0.332	0.274
Adjusted R^2	0.320	0.261
Residual Std. Error	1,407.687 (df = 657)	1,862.976 (df = 649)
F Statistic	27.231*** (df = 12; 657)	20.461*** (df = 12; 649)
Note:		*p<0.1; **p<0.05; ***p<0.01

It appears that there is no effect from the venture capital interaction when it is kept in continuous form. Meaning, the effect from innovation on mobility is unaffected by venture capital funding on a continuous scale. Moreover, this model exhibits an apparent direct impact from our venture capital variable on mobility, bypassing the innovation mechanism. This is not what we set out to explore, but the result is still worth noting.

Taking a step back, the results from our third regression partially support our hypothesis that the effect of innovation on mobility is stronger in regions with high venture capital investment. In fact, this regression result would suggest that innovation has no significant effect at all in areas with low venture capital funding. In theoretical terms, this supports the hypothesis that in areas with high venture investment, we observe a lower value of z from our growth model in (1). However, this result is not robust to our alternative model specification where we use absolute mobility as the dependent variable; in the regression using absolute mobility, we observe no significant effect at all from innovation. Also, when we convert the venture capital variable back to continuous form with imputed lower values, we find no effect from the interaction in both of our dependent variable cases. This may imply that, when doing the binary grouping in our second regression, we are capturing omitted variables and attributing their effect to venture capital funding. Potential omitted variables that are conducive to new entrant success include access to more productive human capital, close proximity to universities, and size of technology industry. This would help explain why our continuous measure of venture capital funding generates an insignificant interaction term whereas the binary version is significant under one of the two model specifications. It is also possible that we are experiencing some sort of information loss with the continuous variable due to data constraints. For these reasons, despite there being some evidence in favor of our hypothesis, we are hesitant to draw any conclusions from this data.

V. A Note on Limitations

It seems imperative that we discuss some of the limitations of these results and of the empirical approach more broadly. Using a simple multivariate regression is not as powerful of an empirical strategy as we might wish to have. The exogenous variation of focus in our analysis is whether or not a commuting zone is characterized by having ample venture capital investment. As stated previously, grouping in this manner opens us up to increased risk of omitted variable bias. Thus, in the binary case, we are likely overestimating the impact of venture capital. Perhaps it would be more accurate to hypothesize that in regions with a strong start-up ecosystem, new entrants (start-ups) are more likely to overtake incumbents, and therefore we might see a greater impact from innovation on mobility in these regions. In this case, the binary definition of the venture capital variable could be interpreted as a proxy for strength of regional start-up ecosystem. Additionally, our venture capital data is not very comprehensive in the first place; we would wish to have data on the true values for each of the commuting zones in the US in order to test our original hypothesis more accurately. Finally, the first result—where we find a positive and significant relationship between innovation and mobility—is not as robust as we would hope for. The argument there would be much more convincing if we had an exogenous shock resulting in a rise in innovation levels at our disposal. If this were the case, we could use a difference in differences model; this would help with the omitted variable issue, as well as the potential concern of backwards causality.

Conclusion

We are left with the conclusion that we cannot make any definitive claims about the impact of venture capital funding on the relationship between innovation and mobility. We did find some evidence supporting our hypothesis, but it failed to replicate across model specifications. We would like to test this same hypothesis under different conditions; namely, conditions in which we had access to better venture capital data and a natural experiment to work with. Despite this, our study makes an important contribution to the literature by showcasing that certain regions may experience the effect of innovation on mobility in differing magnitudes. Further research in this area could lead to important discoveries about the nature of the impact of innovation. Such studies could examine the effect innovation has on other measures of societal well-being, including but not limited to, education rates, life satisfaction, and environmental quality. In such instances, researchers may choose to evaluate how factors other than venture capital can amplify or diminish such effects.

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