Venture Capital and the Transformation of Private R&D for Agriculture

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Abstract:

This paper shows that venture capital (VC) investments in research and development (R&D) intensive startup companies in agriculture has increased substantially from almost nothing in the early 2000s to several billions of dollars by 2018. Such VC investments have not typically been accounted for in estimates of national or global agricultural R&D spending. These investments are supporting new entrants in highly concentrated markets, where incumbents may have been taking relatively incremental approaches to R&D strategy. Such technology-based startups are also an important channel for commercialization of results from public sector agricultural research, in both developed and developing countries. This chapter analyses recent trends in agricultural technology startups and VC investments and seeks to explain the recent upturn. We construct a dataset of more than 4,500 startups located in 125 countries. Econometric analysis on a subset of these startups with detailed financial data shows that the overall supply of venture capital in the economy, growth in agricultural commodity prices, and previous successful exits—including initial public offerings (IPOs) and mergers and acquisitions (M&As)—are all associated with the recent higher levels of VC investment in agriculture.

Key Words:

Venture Capital, Startups, Investment, Innovation, Agriculture

Introduction

Innovation in the agricultural and food system has been fundamental in enabling it to feed the world. Developments in mechanical, chemical, and biological technologies have contributed to productivity gains that have more than doubled outputs of agricultural production over the last 50 years while scarcely changing the aggregate quantity of inputs (Alston et al., 2010). Innovations in harvesting, processing, and other post-harvest steps have also increased the capacity and efficiency of the food system, helping to improve food security and nutritional quality of diets for a growing global population (FAO, 2019).

Innovation in modern agriculture increasingly occurs as a result of formal research and development (R&D) activities, conducted in both the public sector and the private sector. Historically, agricultural R&D has been highly managed. First, it was led by governments supporting agricultural research stations and research at agricultural colleges and universities, beginning in the mid-19th century. By the mid-20th century, an international agricultural research system, supported by philanthropic foundations and international organizations, became a major source of new innovations. Corporate agribusiness and food firms also increased their R&D with the objective of increasing the profitability of their production and marketing activities. While government investments in agricultural R&D have been declining in real terms in high income countries over the last several decades, industry investments in agricultural R&D have increased steadily (Fuglie et al, 2012; Pardey et al, 2016). Globally, annual industry expenditures on agricultural R&D in 2009 were in the range of $10 billion (Fuglie et al, 2011) to $16 billion (Pardey et al, 2015). The most recent available global estimate of industry's agricultural R&D was $15.6 billion in 2014 (Fuglie, 2016). However, all such estimates largely (or only) count publicly listed companies that are subject to public disclosure requirements by securities regulators, and they have largely ignored small and medium size enterprises (SMEs) because they contributed very little to industry R&D.

In recent years, there has been a surge in the founding and financing of startup companies seeking to develop and apply new technologies in agriculture and the food system. These companies are privately-held and have raised significant amounts of equity-based investment from venture capital funds and related private sources such as seed, angel, and private equity investors. According to industry reports, in recent years up to several billion dollars annually have been invested into such agricultural technology (or "agtech") startup companies (AgFunder,

2015, 2019; CBInsights, 2017; Finistere, 2019; KPMG, 2018). While the phenomenon of startup companies or new technology-based firms (NTBFs) introducing new technologies to agriculture is itself not new, recent rates appear to be unprecedented, both in terms of the numbers of startups and the amounts being invested in them. We present evidence that until 2006, the amounts invested in agtech startups globally were relatively negligible, typically less than $200 million per year, then grew steadily for several years, and following 2012 exploded, exceeding several billion annually in recent years. Industry sources, drawing upon a range of different private data sources and industry sector definitions, claim that venture investments in agricultural technology may have been as high as $7 billion in 2018 (AgFunder, 2019). In other words, venture capital and associated private investors could be allocating about half as much toward agricultural R&D today as are the corporate members of the industry.

Yet, accounts vary in term of how prevalent agtech startups are and how much in venture capital is being invested across industry subsectors and across countries. To some extent, this variation is due to the inherent challenges of industry classifications. Established industry classification systems and their categories tend to reflect the structure of incumbent industry sectors—such as seeds, agricultural chemicals, or agricultural machinery. However, many of the recent agtech startups span conventional industry categories. For example, a firm may have its primary industry classification in software while the main application of that software is in on-farm production data management. This variation in accounting is also due to the fact that, historically, private investments in agricultural R&D have been quite low in developing countries (Pardey & Beintema 2001; Pardey et al, 2006). Yet, recently, robust agtech startup activity is being reported in middle- and lower-income countries, especially in the larger emerging economies like India (AgFunder, 2018a), China (AgFunder, 2018b; Gooch & Gale, 2018) and Brazil (Mondin & Tome, 2019; Dias, Jardim, & Sakuda, 2019). It is not clear why this surge in venture investment in agricultural technology has occurred now or what factors account for this recent and dramatic upturn.

This large number of startups and their R&D activities can be expected to impact existing agricultural technologies and industry structure. Startups are tapping new sources of financing to support R&D for agriculture. Compared to established R&D organizations, in both the public sector and the private sector, venture-backed startups are subject to different incentives and constraints and are connected to different professional networks. This allows them, collectively,

to pursue a larger and more diverse range of R&D projects. Some of the R&D conducted by startups may be complementary to R&D by established organizations. Some startups are building upon discoveries made at established R&D organizations, working to transfer or translate those discoveries into market applications. Other startups are contributing new research tools—such as artificial intelligence algorithms or genome editing technologies—that could improve the research productivity of all agricultural R&D organizations. Still, other startups may be directly competing with long established public-sector or corporate R&D programs.

The VC-backed startup is a mechanism to contain the financial risks of prospecting, in the process of R&D reducing the technical and market uncertainties of an innovation. While many startups fail in the attempt, some do prevail in bringing innovation to the market. An increase in the rate of successful startups may help to counter recent trends of increased concentration in agribusiness, in which fewer larger firms are accounting for ever greater shares of private sector R&D (Fuglie, 2016). Venture-backed startups bring Schumpeter's "gale of creative destruction", supplanting some current technologies and companies. Without innovation, concentration can lead to exploitative monopolies, but with innovation, new competition can erode monopoly power.

This paper investigates the increase in the number of new agricultural technology startups. What are the dynamics of entry and growth of new firms that receive venture capital? Where is it occurring globally? Are they concentrated in high income countries? And what are the main categories of technologies they are developing? This paper also explores the causes of the recent growth in VC investments in agriculture. A better understanding of the factors causing this investment will help us to anticipate whether it is merely a transient phenomenon, potentially a "bubble", or whether it constitutes a more enduring shift in the composition and dynamics of agricultural R&D. Other industries, such as software, internet services, and pharmaceuticals, have enjoyed exponential growth and then endured downturns in venture investment, most famously with the bursting of the tech bubble, circa 1999-2000. Yet, today those sectors continue to exhibit an innovation ecosystem that is routinely refreshed by new startups funded by venture capital, in an ongoing cycle. A fundamental question is whether the R&D and innovation system of agriculture is being transformed by the influx of equity-based investments in R&D-intensive startup companies and will come to operate more like these high-tech industries in the long run.

To investigate these questions, we compile a global dataset of 4,552 startup companies in agriculture and 11,998 reported financial transactions, including investments into and exits from these startups. We draw primarily from the proprietary data source of PitchBook (by Morningstar) and augment it with additional company and financial transactions data from other, competing, data sources, including VentureSource (by DowJones) and Crunchbase. The financial transactions data are associated with only a subset of the companies. The financial transactions reported include a range of venture capital, seed, and angel investments, as well as private equity and debt financing. They also include exits by venture investors, such as via initial public offerings (IPOs), mergers and acquisitions (M&As), as well as other types of buyouts. While the transactions data also indicate bankruptcies and closures of the startup firms, reporting of these is clearly incomplete. The transactions data span from 1977 to 2017, allowing us to explore the startup life cycles and exit outcomes over time and across multiple technologies (e.g. biotech vs software) and subsectors of agriculture (e.g. inputs vs. outputs, or crops vs. livestock).

These compiled data give us a global view of agtech startup and investment activities. We see exponential growth in the number of the agricultural startups between 1977 and 2017. The largest share is in the United States (33 percent), followed by the European Union (23 percent), with the remainder (44 percent) located elsewhere in the world. Significant numbers are in emerging and developing economies, such as India (5 percent), China (4 percent), and Brazil (2 percent). In terms of the technologies being developed, about one third of the new startups involves computer, IT, and data related technologies, another third involves biotechnology, breeding, genetics, or animal health, and the rest encompass a wide range of other technologies, applications, and business models, including marketing and sales.

This paper looks first at the economic literatures on agricultural R&D and on venture capital investments. We then introduce the data set on agricultural technology startups. The broader sample is used to track overall trends, such as founding rates, startup locations globally, and startups by industry or technology categories. The narrower subset with associated investment data is used to analyze factors associated with the growth in investments, both at the firm level and at the industry level. Results suggest that recent surges in agricultural commodity prices together with higher amounts of venture capital being invested overall, facilitated by signals from successful exits, have led to the surge in venture capital investments in agriculture.

Literature Review

Financing of R&D in Agriculture

There is a robust agricultural economics literature on the institutional and financing aspects of agricultural R&D (Alston et al, 2010; Huffman & Evenson, 2006; Pardey, Alson, & Ruttan, 2010; Sunding & Zilberman, 2002). Relative to other industries, agriculture has long had a high ratio of public sector to private sector R&D. Pardey and Bientema (2001) tracked spending over several decades and estimate that in 1995, total global agricultural R&D was $33.2 billion, of which 65 percent ($21.7 billion) was by public sector sources (defined as research conducted by or funded by governments, academics, or non-profit organizations) while 35 percent ($11.5 billion) was by the private sector (defined as profit-motivated R&D by privately or publicly held, as well as state-owned companies). Five years later, in 2000, global total spending on agricultural R&D was only slightly higher, at $33.7 billion, and the sectoral shares had adjusted slightly, with approximately 60 percent conducted by public sector and 40 percent conducted by private sector (Pardey, et al, 2006).

Several key trends have been observed in the composition of agricultural R&D globally. The share of global agricultural R&D conducted in middle- and low-income countries is about 45 percent (versus 55 percent conducted in high-income countries), which is a much higher share than overall R&D conducted in low- and middle-income countries, which is 22 percent versus 78 percent in high-income countries (Pardey et al 2015). However, of the agricultural R&D conducted in low- and middle-income countries, very little of it is in the private sector. Historically, private sector R&D in developing countries was very low. In 1995 of the agricultural R&D conducted in developing countries, only 5.5 percent was by the private sector (Pardey & Bientema, 2001).

Over the last two decades, agricultural R&D has grown steadily but unevenly both by sector and by geography. In the United States and other high-income countries, public sector spending is growing only very slowly in nominal terms, and has declined in real terms (Pardey et al, 2016). At the same time, public-sector spending has surged in middle-income countries, particularly in China (Hu et al, 2011). Private-sector R&D has grown steadily, both in high-income and middle-income countries. Private expenditures on agricultural R&D in 2009 were on the order of $10 billion (Fuglie et al, 2011) to $16 billion (Pardey et al, 2015), with differences in the estimates depending largely upon which industry subsectors of the agricultural

and food system are included or how data for unobserved spending by small and medium sized enterprises (SMEs) is estimated (Fuglie, 2016). The most recent available global estimate of private sector agricultural R&D was $15.6 billion in 2014 (Fuglie, 2016). At the same time, private sector agricultural R&D has become increasingly concentrated in the hands of fewer larger companies (Fuglie et al, 2011).

Such accounts, however, have been based primarily on R&D spending by publicly listed companies. It has not been feasible nor, frankly, relevant to be concerned about R&D spending by small or medium enterprises, including venture capital backed companies. While biotechnology startups were observed to have contributed significantly to the rise of genetic engineering in agriculture in the 1980s and 1990s (Fuglie et al 2011; Fuglie 2016; Graff, Rausser, & Small, 2003) levels of R&D spending and other financial data on such privately-held companies are relatively inaccessible, as they are not subject to the same reporting requirements as publicly traded firms. Moreover, the relative amounts of R&D spending contributed by SMEs have historically been negligible (Fuglie 2016).

Venture Capital Investments

Dixit and Pindyk (1994) developed the standard methodology used to assess investment decisions taking uncertainty and irreversibility into account. They argued that while the net present value approach is meaningful when considering whether to make an investment at a given moment in time, in most realistic situations, investors also have to decide about the timing of their investment and therefore have to take into account the randomness of key variables such as cost. The timing of an investment is triggered when the key random variable exceeds a certain threshold, also known as a hurdle rate. A good example of this approach in agriculture is the uncertainty around investing in new irrigation technologies due to agricultural prices and weather uncertainty (Carey and Zilberman, 2002). Farmers only adopt new irrigation technologies when prices exceed a certain threshold.

The same basic logic applies to VC investments in agricultural technology startups. Even though venture capital investments have been feasible for decades, it was only after 2010 that they increased significantly (see Figure 4). Several factors may have affected the hurdle rate, such as an increase in the ratio of agricultural prices to non-agricultural commodity prices, the occurrence of large exit events in highly visible ag technologies, the emergence of new

technological opportunities based on advances in enabling technologies (such as cheaper genome sequencing, genome editing, or data capacity of sensors and networks), as well as changes in (agricultural) labor markets both in high income and middle income countries.

In general, it has been shown that the dynamics of venture capital markets are driven by several measurable factors, including expected investment returns, the overall health of the economy, industry characteristics, and company financial performance variables (Gompers and Lerner, 2004). Venture capital funds that invest in agriculture are no different. Fundamentally, they are seeking returns on investment. Investors compare performance across industries, aspiring to identify high expected returns. Large positive swings in agricultural commodity prices would be expected to shift the supply of venture capital investments towards startups in this industry. Changes in commodity prices such as observed between 2007 and 2014 might have played a role in the increase of the supply of venture capital investments in agriculture. Even though Deloof and Vanacker (2018) observe that Belgian startups founded during the 2007 crisis had greater chance of facing bankruptcy.

Gompers and Lerner (2004) point out the greater number of rounds and larger amounts of investments go into high-tech industries, such as computers and biotechnology, compared to other more traditional industries. Even though agriculture, broadly speaking, may be considered a traditional industry, most venture capital investments in the sector are targeting high technologies, such as geospatial technologies, digital sensors, or robotics for precision agriculture, agricultural biotechnology, vertical farming, alternative protein products, artificial intelligence driven decision-making tools, and big data for supply chain management (AgFunder 2014; Graff et al, 2014; Rausser et al., 2015). Regulations influence investments in agricultural technologies as well. For example, regulations imposed by different countries or regions (such as the Europe Union) on gene editing might lead to big changes in agbiotech investments, with potential market uptake depending on whether other countries will follow European or American standards towards this technology (Rausser et al., 2015).

Venture Capital Exits

There is also a large literature examining exit outcomes as a key factor in the functioning of venture capital markets. Large exit events, including initial public offerings (IPOs) and mergers and acquisitions (M&As) of startups may foment further investments. There is evidence on the

positive effect of the size of IPO (Jeng and Wells, 2000) and M&A (Felix et al., 2013; Groh and Wallmeroth, 2016) on subsequent venture capital investments. In agriculture, the acquisition of the Climate Corporation by Monsanto in 2013 for $930 million and of Blue River Technology by the John Deere in 2017 for $305 million may have stimulated subsequent investments in other agricultural technology startups (Rausser et al. 2015).

The literature investigating startup exits identifies key factors that affect both new company starts and existing companies' survival, such as real interest rates, other macroeconomic variables, company sizes, and industry-specific variables (Homes et al., 2010; Giovannett et al., 2011). Audretsch (1994; 1995) also show that such variables can determine the exit outcome, finding, for example, that startup size is related to chance of exit while industry growth rate is not. Yuri and Zarutskie (2012) compare VC-backed companies and non-VC-backed companies using a matching technique and a multinomial logit model. They find evidence that companies with venture capital investors have a higher likelihood of resulting in an M&A or IPO exit and lower likelihood of a failed exit, all compared to the base category of firms with no exit, controlling for industry-specific characteristics and year fixed effects. Gompers and Lerner (2004) present extensive discussion on the likelihood of going public (IPO), showing that generally better industry conditions, as captured in an industry equity index (e.g. biotechnology index), are positively associated with the number of IPOs.

On the determinants of venture capital funding, the main goal this paper, Groh and Wallmeroth (2016) and Jeng and Wells (2000) investigate both developed countries and emerging markets. Groh and Wallmeroth (2016) show that the share of venture capital investments in emerging markets increased from 2.4 percent in 2000 to 20.8 percent in 2013. Previous and contemporaneous exit outcomes are directly associated to VC investments. While Groh and Wallmeroth (2016) find evidence that M&A impact venture capital funding positively, Jeng and Wells (2000) find that IPOs play a role on determining venture capital investments at the later stages of the startup lifecycle. These investments into technologies that may be related to the agricultural industry are also location-specific (Kolympiris and Kalaitzandonakes, 2013; Pe'er and Keil, 2013; Kolympiris et al., 2015; Kolympiris et al., 2017). This—combined with the observation above that overall agricultural R&D activities have shifted toward emerging markets—makes it reasonable to expect that the share of venture capital investments in agriculture has shifted towards emerging markets as well.

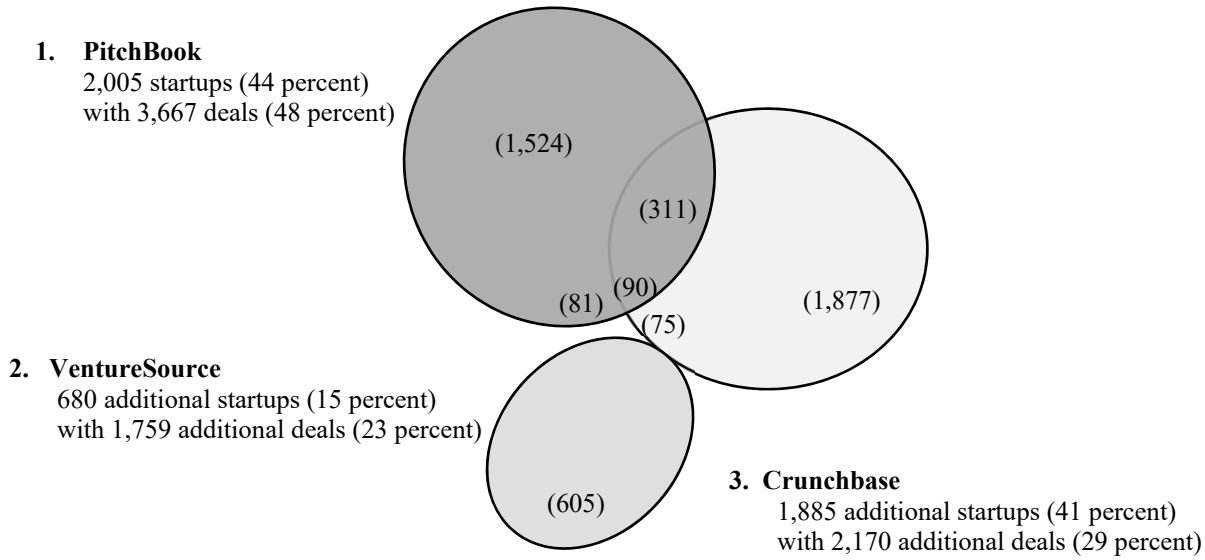
Data on Venture Capital Investments in Agriculture

The data for this "first look" analysis of venture capital investment in agriculture is drawn from proprietary business databases. Of these, the industry standard is generally regarded to be PitchBook, a financial database focused on venture capital and private equity investing, owned by MorningStar. This analysis is based on data from PitchBook, augmented with data from two other sources: VentureSource and Crunchbase, From each, two types of data are available, linked in a one-to-many relationship: one set of data for companies and a second set of data for transactions or deals involving (at least some of) those companies. Our initial sampling, drawn from PitchBook, included 2,005 companies founded in the 40 years from 1977 to 2017, and their corresponding 3,667 deals, as designated by PitchBook's "AgTech vertical" industry category.[1]

A comparison of agtech company data listings across these data sources was undertaken with an expectation that overlap among the data sources would allow for cross-validation of firms and deals. However, as Figure 1 illustrates, we found only minimal overlap of ag tech company listings across data sources. Just 557 (12 percent) of the total companies identified are listed in more than one data source, and only 90 (2 percent) of the total companies identified were listed in all three data sources. VentureSource, by DowJones, had an additional 680 companies with 1,759 additional deals—from their "Agriculture and Forestry" industry category—that were not included in PitchBook. Crunchbase—from their "Agriculture" industry category—had an additional 1,885 companies beyond those listed in either PitchBook or VentureSource, and had data on 2,170 additional deals for a subset of those companies. This pattern of data availability suggests that industry reports based upon one primary data source (such as AgFunder, 2015, 2019; CBInsights; Finistere; KPMG; etc) each provide only a limited and separate sampling of overall venture investments in agriculture.

[1] PitchBook defines an "industry vertical" or "vertical market" as "*a more specific industry classification*" that "*identifies companies that offer niche products or fit into multiple industries*" or that represent "*new fields with promising companies that attract investors*." PitchBook defines the AgTech vertical to consist of "*Companies that provide services, engage in scientific research, or develop technology which has the express purpose of enhancing the sustainability of agriculture. This includes wireless sensors to monitor soil, air and animal health; hydroponic and aquaponic systems; remote-controlled irrigation systems; aerial photo technology to analyze field conditions; biotech platforms for crop yields; data-analysis software to augment planting, herd, poultry and livestock management; automation software to manage farm task workflows; and accounting software to track and manage facility and task expenses.*" (PitchBook, 2019)

Figure 1. Data on new venture-funded startups in agriculture:
Primary source is PitchBook, augmented by VentureSource and Crunchbase



The company data from these sources provide such basic information as founding date, physical and virtual addresses, current number of employees, a company description, and other firm-specific variables. However, not all companies provide full information for each of the data fields within any one of the data sources, and, moreover, each data source has its own approach to certain pieces of information—such as key dates, addresses, or how they categorize companies by industry, market, or technology.

The deals data from these sources contain information such as the target company's name, the type of investment, the announcement and/or closing date of investment, and, for a subset of the deals, the amount transacted. Variation in reporting across the three data sources includes variation in dates, currencies, and how they categorize deal type.

After considerable data cleaning and harmonization, our combined data set contains 4,552 companies and 7,596 unique reported deals, including investments or "money-in" deals, successful exits or "money-out" deals, plus closures or bankruptcies. We derive about half of the data on companies and deals from PitchBook, and the other half from VentureSource and Crunchbase. Of these, Crunchbase was helpful in identifying a wider range of startups companies, particularly internationally, but was not able to provide as much coverage of deal information for the identified firms. Overall, deals data are associated with only 1,584 (35

percent) of the companies in the combined data set. Of the subset of companies with deal information, 1,366 (29 percent of the total) report at least one investment with the amount disclosed (others report deals that occurred, but do not disclose amounts), and 1,092 (24 percent) have an identified exit deal. Given these discrepancies in the availability of deal information the analysis is undertaken in in two parts.

First, we summarize major industry trends using the full data set of 4,552 companies. Second, we summarize investments and exits for the 1,348 startups with accompanying deals data that discloses amounts, and we analyze the economic factors that may have led to the recent growth in those investments. Arguably, given the skewed nature of valuations and investments in venture capital markets generally, together with a natural propensity to report information on larger, more significant investments and exits, it stands to reason that the 29 percent of companies with disclosed deals represent a considerably greater share than that of the overall financial activity in the industry. Regardless, this data is necessarily an underrepresentation of the overall financial activity in the industry. Yet, drawing from a variety of available data sources, the following analyses are based on a broad, representative sampling of private investment activity across agriculture globally.

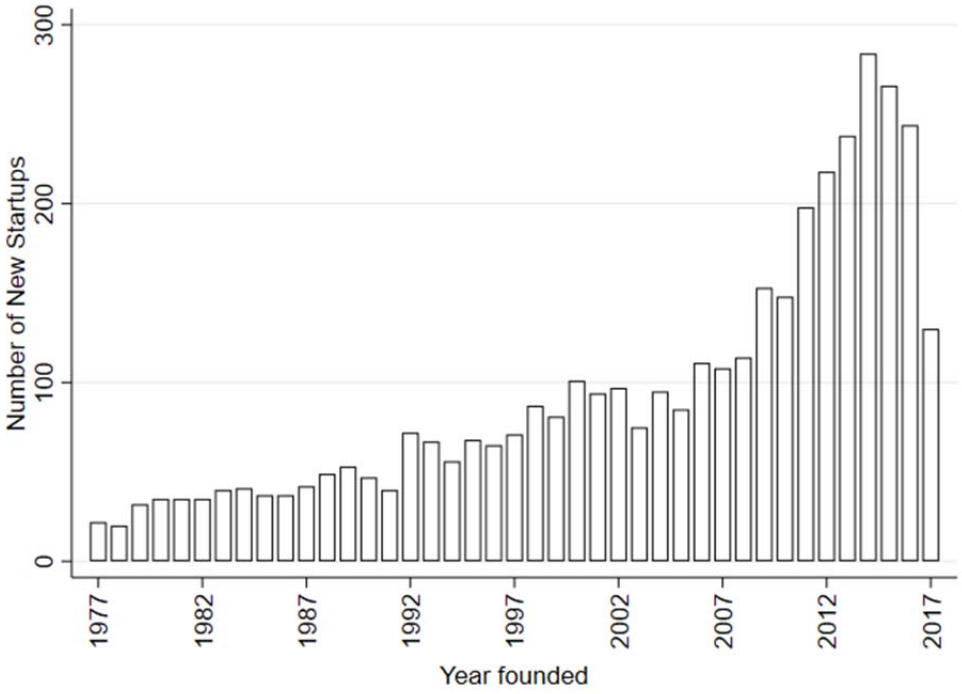
Full combined data set of companies: global summary statistics

For most of the 4,552 companies in the combined sample, founding date is available for most. For those companies with founding date missing but for which deal information is available, the date of the first deal is used as a proxy for the start year. Figure 2 plots the number of new venture-funded startups by founding year.

Qualitatively, there appears to have been three phases of growth in agtech startups. First, from 1977 to 1991 we see steady, slow growth, with between 20 to 50 agtech startups globally each year, although, this time period precedes the full data coverage for some of the countries and/or data sources on which this data set draws. In the second phase, from 1992 to 2008, the growth rate appears to have increased, yet it also appears to be more volatile—characteristic of the wider tech sector during this period—with a downturn for several years following the bursting of the tech bubble in 2000. Third, starting in 2009, growth in agtech startups experienced a sharp

increase that, arguably, continues until the end of the time frame of this analysis despite the right-hand truncation seen here.[2]

Figure 2. New venture-funded startups in agriculture, 1977-2017

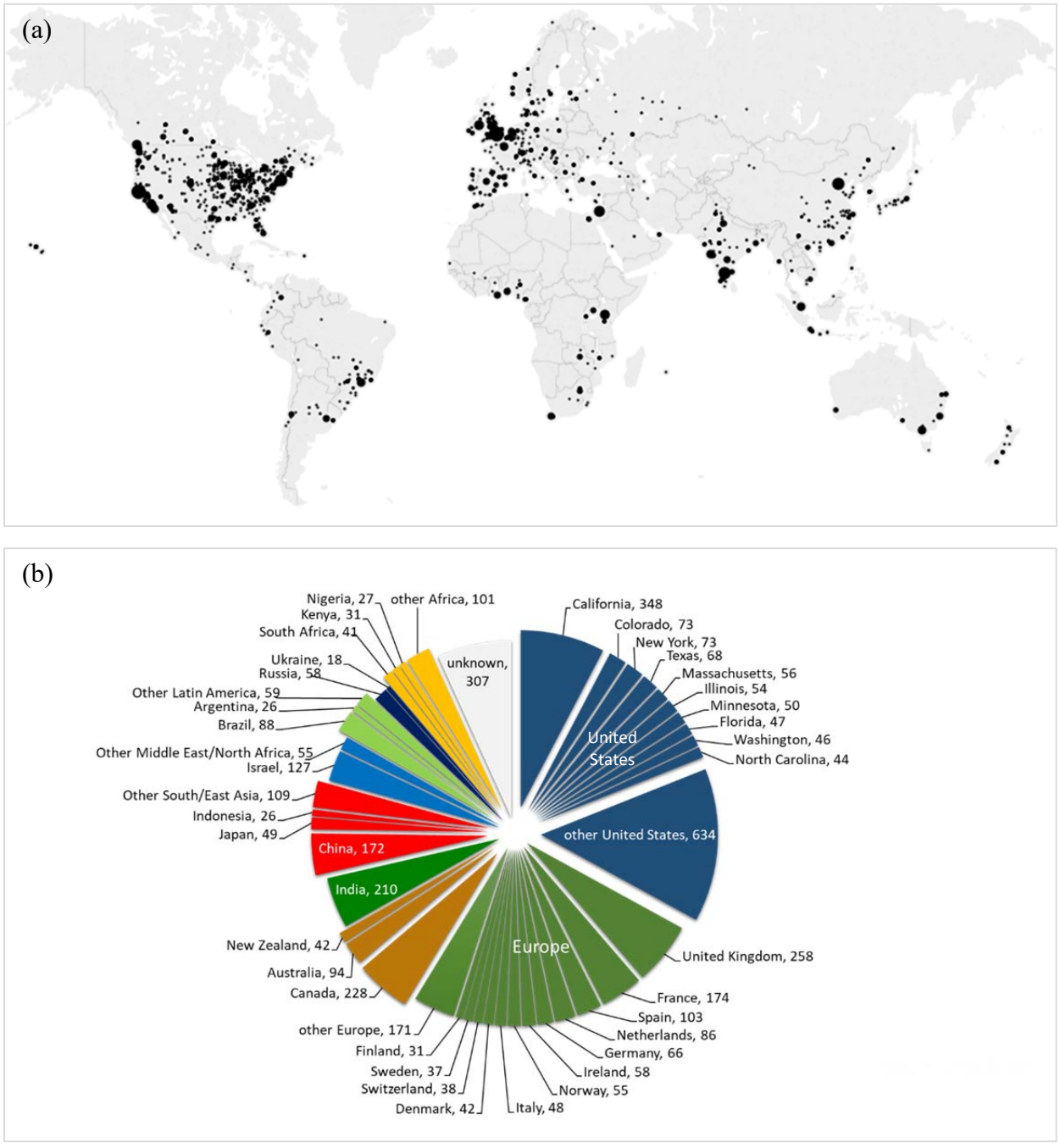


The overall sample of 4,552 companies also includes data on physical address, which enables analysis of the geographical distribution of agtech entrepreneurship globally. We find 1,483 startups in the United States, which accounts for about 33 percent of the global sample (Figure 3). Within the United States, by far the most are in the state of California (348), with other leading states including Colorado, New York, Texas, Massachusetts, and Illinois. Of the U.S. startups, 320 were located across the 11 Midwestern states that encompass the highly fertile U.S. "corn belt" region. The European Union has 1,063 agtech startups, accounting for about 23 percent of the global total, led by United Kingdom (with 261), France (173), and Spain (102). Canada is home to 228 startups (5 percent of the global total). Among the emerging markets, India stands out with 210 startups, followed by China with 172. South American countries have 144 agtech startups in the sample, led by Brazil with 88. Venture-backed agtech startups are even found in Africa, with the most in South Africa (41), followed by Kenya (31) and Nigeria (27).

[2] The apparent decline in startups after 2014 is, arguably, due to truncation in the data. New companies generally get reported to these data sources upon their first formal equity-based investment, which can occur up to several years following the founding of the company. Industry reports, such as AgFunder (2019) show steady continued growth in startup activity through 2018.

The pattern of VC-funded startups follows the growth pattern of VC in developing countries identified by Groh and Wallmeroth (2016).

Figure 3. The global scope of new venture-capital-funded startups in agriculture, 1977-2018: (a) global density mapping, by city and/or postal code, and (b) global share, by country/region.



This global distribution of agtech startups appears to track somewhat more closely with the pattern of public sector agricultural R&D, with a significant share in emerging and developing economies (Pardey et al, 2016), compared to the pattern of private sector agricultural R&D, which is more heavily concentrated in high income countries (Fuglie, 2016).Categorization of startup companies by industry—or of innovations by technology field—has long been a fraught exercise. Of the three data sources, each provides several data fields describing the company, its market activities, and the technologies it is developing. However, the descriptions of companies are very heterogeneous, even within the same data field from the same source. Even standardized industry category variables, which are more consistently reported within each data source, are not readily comparable across the three data sources. We therefore construct a common categorization for the startups in the combined sample, drawing upon the full range of these descriptive data fields across all three data sources, based upon industry observations (see Graff et al, 2014, and AgFunder, 2019), as detailed in the Appendix.

Table 1. Industry and technology categories describing agtech startups

Category	Number of startups with activities described by each category
Agricultural input technologies or services	2,482
Software, data, and IT	942
Devices or sensors	430
Biotech, genetics, or health	918
Chemicals	230
Equipment or machinery	302
Ag input distributors, dealers, or co-operatives	678
Ag producers or farms	467
Marketing, processing, manufacturing	730
Consumer products or services	105
Business and financial services	539
Online services and content	471

Other	1,165

N=4,552 firms, of which 1,226 are identified with two or more categories

It is important to note that the categories we develop are not exclusive. By their very nature, startups often span more than one industry or technology. Of the 4,552 startups in the data set, 1,226 (27 percent) are categorized in more than one category: of these 1,048 are categorized in two categories, 161 are categorized in three, and 15 startups are assigned four. For example, we have a startup that is developing sensors with specialized data management tools to conduct high-throughput phenotyping to decipher crop genetics: such a firm would be labelled with three of these categories: (1) devices or sensors, (2) software, data, and IT, and (3) biotech, genetics, and health. While such an approach does result in multi-counting of firms by categories, it is not an uncommon practice.[3]

Table 1 displays the number of startups described by each of the categories we developed. Just over half of the startups in the data set are involved in some form of *agricultural input technology or service*, which in turn encompasses a number of different technology-based sub categories. The two largest of these are *software and data* (which describes 942 startups) and *biotech, genetics, or health* (which describes 918 startups). Companies identified by one or both of these categories—software and biotech—attracted more than 60 percent of the venture investments made in the industry in 2016.

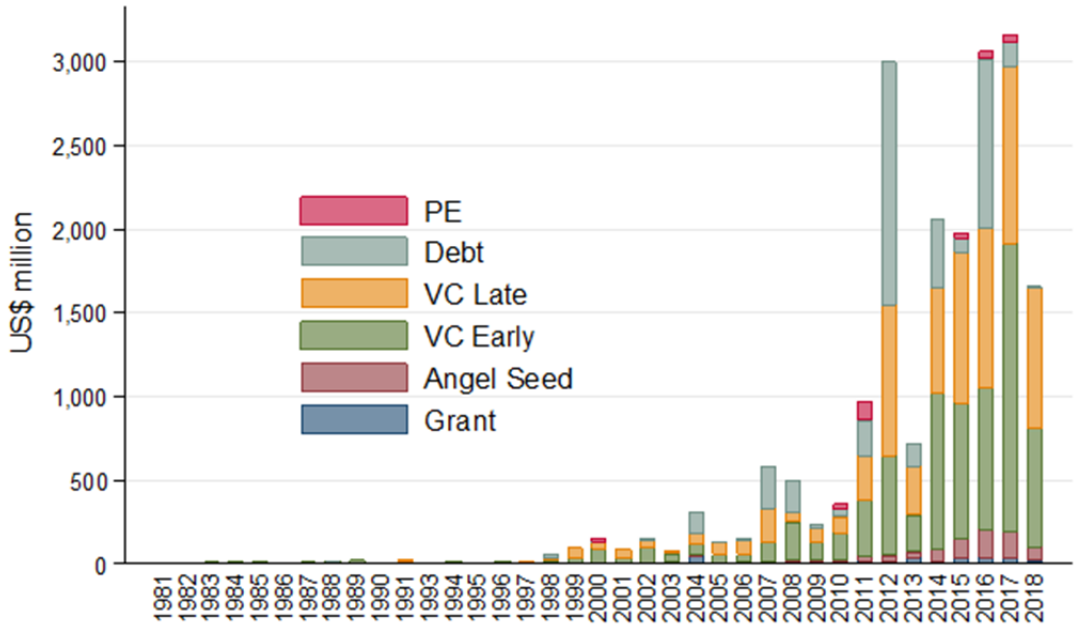
Subsample of companies with reported deals

Of the 4,552 companies in the overall data set only 1,584 (35 percent) are associated with the 7,596 reported deals (which, again, include investments, successful exits, and reported closures or bankruptcies). Moreover, of these reported deals, many do not disclose the amount of the deal. To analyze investment and exit trends, we narrow to a sub-sample of just those 1,367 startups (29 percent of the overall data set) that report at least one venture-type money-in investment with a disclosed amount. This means that we are therefore underestimating the number of startups, the values of investments, as well as the numbers and values of exits for the industry.

[3] For example, under the International Patent Classification (IPC) system, multiple patent classifications can be assigned to a single patent.

This analysis considers, however, the full profile of investments received by those startups that receive any investment from venture capital. If a company received at least one venture-type investment, then all additional money-in investments received by that same startup are considered in this analysis, including grants, angel and seed stage investments, early stage VC, late stage VC, debt, and private equity investments. (Companies with only private equity investments were dropped from the sample). Figure 3 displays the total money in investments by type and year for those firms.

Figure 4. Investments into agricultural technology startups 1981 to 2018, by type of investment



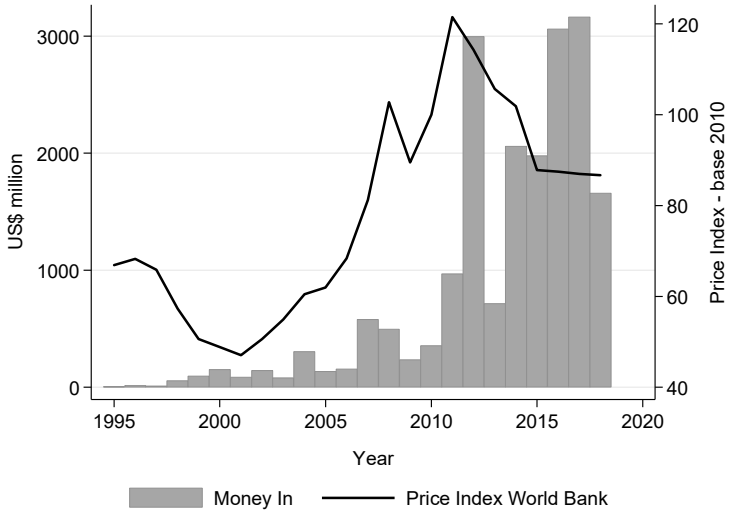
Note: PE=private equity; VC=venture capital

Following the sharp increase in new startups in 2009 (Figure 2) investments exhibited a sharp increase starting in 2011 (Figure 4). Given that these are all firms that receive at least some venture capital, these data suggest that venture capital in fact represents most of the money raised. Even though absolute amounts increased substantially, the composition of investments has been stable between early-stage and late-stage VC. This data series also most certainly exhibits right hand truncation, as some of the data downloads occurred in the middle of 2018. Industry sources indicate that 2018 was a record high year for agtech venture investments (Agfunder, 2019).

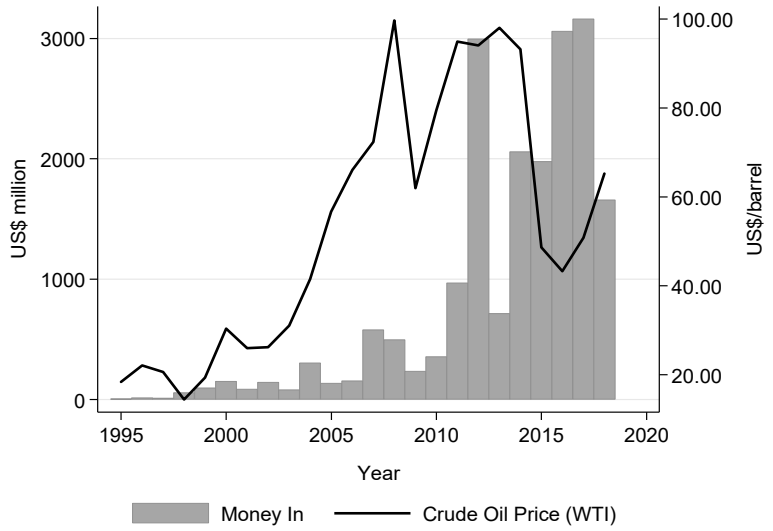
The growth in investing the agriculture industry may have been driven by high commodities prices during the downturn in the economy around the 2007-8 financial crisis. Figure 5 displays an index of agricultural commodity prices and crude oil prices over time, each plotted against our data on total investments into agtech startups (from Figure 4). There appears to be a direct (albeit lagged) relationship between these prices and agtech investments.

Figure 5. Investments in agricultural technology startups plotted against:

(a) agricultural commodity prices (base year 2010=100)



(b) oil prices



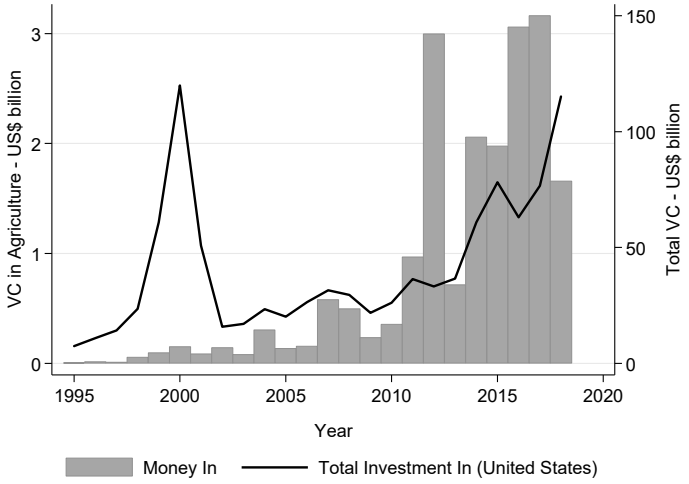
Analysis of factors associated with increased venture capital investments in agriculture

There are several possible explanations for the sharp increase in agricultural technology startups beginning in 2009 (Figure 2) and the sharp increase in private investments into those companies beginning in 2011 (Figure 4). The simplest hypothesis, following the logic of Dixit and Pindyk (1994), is that prices pushed potential return above a critical threshold. Agricultural commodity prices, indeed, increased strongly in 2007 and 2008 and then, after a correction in 2009, surged to even higher levels from 2011 through 2014 (Figure 5.a).

A more nuanced hypothesis is that the ratio of commodity prices in agriculture to prices in other sectors of the economy, particularly energy, may have diverted investments toward agriculture. "Cleantech" investment funds—which had focused primarily in the energy sector, encouraged by high energy prices—may have discovered agriculture when investing in biofuel innovators. Crude oil prices faced a sharp increase in 2007 and 2008, turned down in 2009, and rebounded and remained around US$100/barrel from 2011 through 2014, at which point they fell back to less than US$50/barrel within a year. As oil prices dropped, investors in clean-tech may have pivoted toward opportunities in agriculture as agricultural commodity prices may have been expected to remain high longer than energy prices.

There is also likely a supply side factor, given that overall VC investments in the economy increased steadily during this time period. Figure 6 shows that growth in investment in agtech plotted against total VC investment in the United States (as according to PWC, 2019). Investment in agtech is correlated with total VC investments, yet growth in agtech investment grew at a faster rate, particularly in the pivotal years of 2010-2016. Thus, an additional hypothesis is that a greater supply of VC and lower costs of early stage investing in this time period pushed VC investing into adjacent industries from its traditional core of software, computer/networking equipment, online businesses, and biotechnology (Ewens, Nanda, & Rhodes-Kropf.2018).

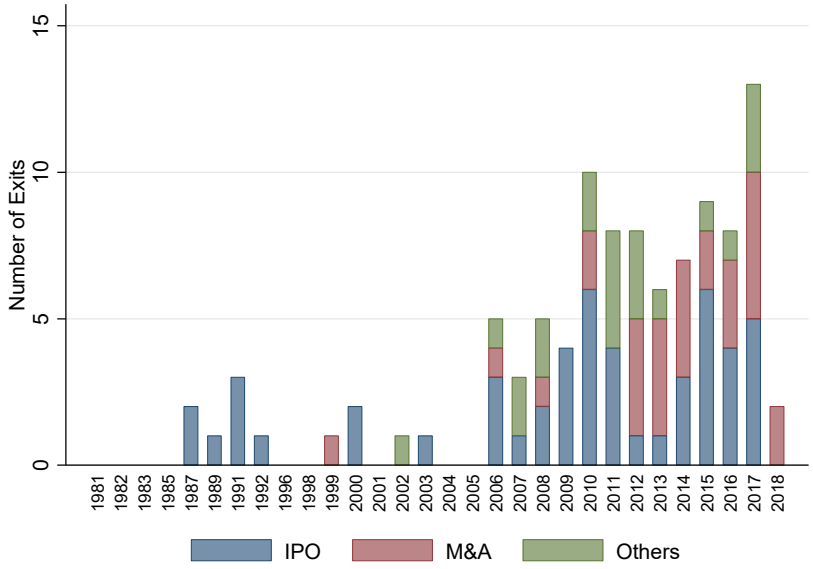
Figure 6. Investments in agricultural technology startups plotted against total VC investments in the United States



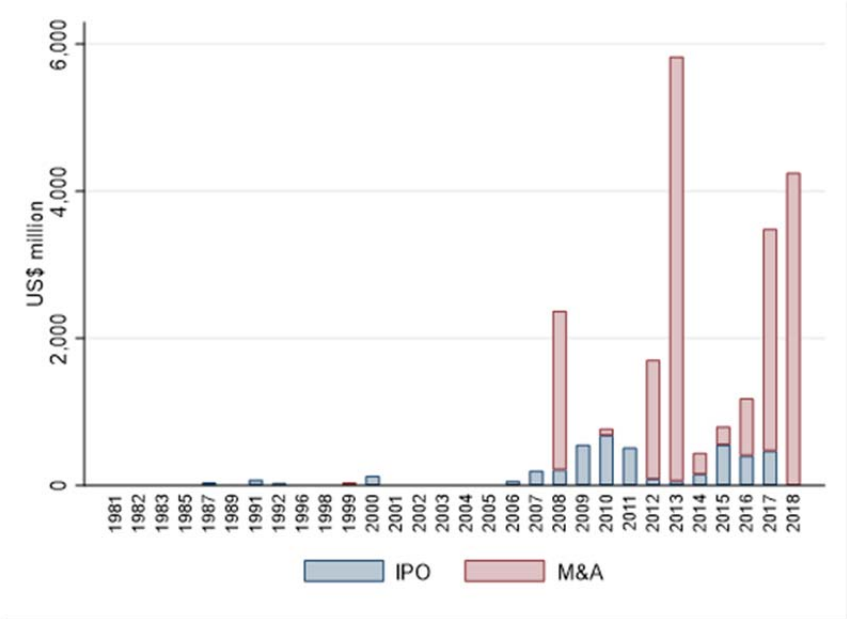
Finally, market signals from successful exits may have played a role. The returns for VC are realized upon exiting from initial investment in startups. The most desired outcomes for VC investors are an initial public offering (IPO) or a merger or acquisition (M&A), as these types of exits generate the largest payoffs. Other exit outcomes, such as a management buyouts or asset acquisitions, might merely return the initial investment via sale of the startup's assets. Gompers and Lerner (2004), Jeng and Wells (2000), and a literature spawned by such studies, present evidence that successful exits influence subsequent investments.

Anecdotally, there were several large exits from agtech companies in the years around the upturn in venture investment—including the US$283 million IPO of Agria in 2007, the EUR 1.9 billion private-equity buyout of Arysta LifeScience in 2008, and the US$279 million IPO of Digital Globe in 2009, and the US$980 million acquisition of Climate Corp by Monsanto in 2013. According to the data, a regular rhythm of IPOs and M&As began in 2006, with significant returns first logged in 2008 (Figure 7) coinciding with the sharp increase in the numbers of new startups (Figure 2) and investments (Figure 4). In agtech, it appears that M&As have generated much larger returns for VC investors than IPOs (Figure 7.b). These patterns corroborate the idea that the occurrence of IPOs and M&As signal returns being made in the industry, thus helping to attract new investors and investments to the industry.

Figure 7. (a) Exit events by agricultural technology startups, 1981-2018



(b) Money out from IPO and M&A exits by agricultural technology startups, 1981-2018



Methods

A preliminary test of these hypotheses is conducted at both the firm level and the industry level. The regression framework used to test at the firm level is describe by Equation (1):

$$y_{it} = \alpha + \beta_1 P_{1,t-k} + \beta_2 P_{2,t-k} + \beta_3 VC_t + \delta_1 ee_{t-k}^{m\&a} + \delta_2 ee_{t-k}^{ipo} + X_i\theta + u_{it} \quad (1)$$

where the dependent variable is the sum of *realized* investments received by a startup *i* within year *t*. If a startup received more than one investment in a given year, those investments are summed, but if a startup did not exist or simply received no investment in a given year (y_{it}=0) the observation is dropped. In Equation (1), the P_{1t}. are agricultural commodity prices, lagged *k* years, for which World Bank and FAO agricultural commodity price indices as well as nominal soybean prices were used. The P_{2t} are nominal oil prices. VC_t is total annual venture capital investments in the United States. The exit variables, $ee_{t-k}^{m\&a}$ and ee_{t-k}^{ipo} measure the IPO and M&A exits, *k* years prior to year *t*. The X_i are control variables. The sample is very heterogenous, including firms of different sizes, at different stages in the startup lifecycle, across different countries and industry categories. To control for these, dummy variables are added for the United States and Europe. Firm size is accounted for with an ordinal variable based on numbers employees ranging from 0 for "very small" to 5 for "very large". Company age controls for stage in the startup lifecycle. Finally, u_{it} is the random error term clustered at the firm level.

The sample incorporates investment activity from 1995 to 2018, since data for the independent variables of oil prices and total VC investments were available only after 1995. We build an unbalanced panel that consists of 2,364 observations involving 1,348 startups. A balanced panel of 1,348 startups over this 24-year time period would consist of 32,352 observations with positive values for only about seven percent of those observations. Yet, most of the firms were founded after 1995, with the frequency of firms entering the dataset increasing toward the end of the time period, according to the trend illustrated in Figure 2.

To test hypotheses regarding venture investments at a more aggregated industry level (as described in Table 1) a similar model to equation 1 is estimated, but the dependent variable, instead, is y_{ct}, the annual sum of investments for all startups in industry category *c* for year *t*.

There are reasons to believe that factors affecting investment may vary across industry or technology. As already noted, 60 percent of agtech investments in 2018 were made in either the software/data or biotech/genetics categories. Some of the startups in the sample are categorized in more than one industry, due to the multidisciplinary nature of the technologies being developed or due to integration across markets. We therefore split such startups' investment amounts across the relevant categories (e.g. if startup A appears in two categories, we multiply its investments in year *t* by 0.5 and allocate to both categories for year *t*). All other dependent variables are the same as defined for Equation (1). We build a balanced panel of 11 industry categories over 24 years from 1995 to 2018 and estimate a fixed effects model.

Regression results

Table 3 presents regression results for four versions of the firm level analysis described by Equation (1). The first set of regressors examines the relationship between investments and commodity prices, using, in this case, nominal soybean prices and nominal crude oil prices. Both contemporaneous and lagged prices are considered, expecting investors may be responding to cumulative market trends over several years, not just immediate price fluctuations. We also focus the analysis on the differential effect of these price variables in the period after 2000 by interacting each with a date range dummy variable.

The estimation results in Table 3 corroborate observations from the summary statistics in Figures 5.a and 5.b that agricultural and energy prices are positively associated with investments in agtech startups, especially after 2000. The fact that investments become more responsive to prices after 2000 suggest that growing commodity prices may have shifted attention of venture capital investors. Results are robust across versions of the model, even when prices are lagged. Although oil prices are statistically significant only when added contemporaneously, the negative sign persists across estimations. It suggests that an increase in oil prices lead to lower investments in startups in agriculture, or conversely, investments in agtech startups may have been stimulated when oil prices fell.[4]

[4] In additional regressions not included in Table 3, we tested the effect of the ratio of agricultural commodity prices to oil prices, with a larger ratio indicating a potentially greater return in agriculture compared to energy. We find a strong positive effect of the price ratio on the size of investments when limited to the 2000-2018 window. The coefficient on the price ratio over the entire timeframe is, however, not significant.

Table 3. The effect of commodity prices, exits, and total VC supply on agtech investments made annually over the period 1995-2018 at the firm level, with fixed effects

	Dependent variable: Amount invested in firm in a given year			
	Models			
Independent Variables:	1	2	3	4
ag prices	-0.0075	0.0155		
	(0.0274)	(0.0297)		
ag prices*dummy[2000+=1]	0.0458***	0.0244***		
	(0.0142)	(0.0153)		
lag(ag prices)			-0.0331*	-0.0192
			(0.0177)	(0.0184)
lag(ag prices)*dummy[2000+=1]			0.0323**	0.0193
			(0.0133)	(0.0133)
oil prices	-0.1804**	-0.1010		
	(0.0832)	(0.0823)		
lag(oil prices)			-0.0092	0.0255
			(0.0548)	(0.0531)
lag(IPO amounts)	0.0083***	0.0053*	0.0112**	0.0106**
	(0.0032)	(0.0030)	(0.0047)	(0.0047
lag(M&A amounts)	0.0011**	0.0002	0.0006	0.0001
	(0.0005)	(0.0005)	(0.0004)	(0.0004)
total VC		0.0001***		0.0001***
		(0.00003)		(0.00003)
R^2	0.11	0.11	0.11	0.11
N	2364	2364	2364	2364

Note: Standard errors in parenthesis. *** for 1% significance, ** for 5% and * for 10%. All lagged variables are lagged only one period. IPO, M&A and Total VC for the United States are in US$ million; Ag. Price is the Soy price and it is nominal prices in US$/metric tons; The Oil Price is the West Texas Intermediate (WTI) - Cushing, Oklahoma, Dollars per Barrel, Annual, Not Seasonally Adjusted available at FRED. Dependent variable ($ deals size) is in US$ million. All regressions include industry and location fixed effects.

Table 4. The effect of commodity prices, exits, and total VC supply on agtech investments made annually over the period 1995-2018 at the industry level, with fixed effects

	Dependent variable: Amount invested in industry category in a given year			
	Models			
Independent Variable:	8	9	11	12
ag prices	0.3951*	0.5351**		
	(0.2047)	(0.2297)		
ag prices*dummy[2000+=1]	0.3469*	0.2634*		
	(0.1656)	(0.1444)		
lag(ag prices)			0.2735*	0.3184*
			(0.1546)	(0.1658)
lag(ag price)*dummy[2000+=1]			0.2133*	0.1217
			(0.1213)	(0.0941)
oil prices	-3.1985*	-2.9255*		
	(1.5481)	(1.4775)		
lag(oil prices)			-1.6126	-1.0554
			(1.0735	(0.9004)
lag(IPO amounts)	0.1335**	0.0853**	0.1635***	0.1372***
	(0.0502)	(0.0363)	(0.0497	(0.0427)
lag(M&A amounts)	0.0178**	0.0097	0.0093	0.0019
	(0.0074)	(0.0061)	(0.0078	(0.0077)
total VC		0.0008**		0.0007**
		(0.0003)		(0.0003)
R^2	0.31	0.32	0.29	0.30
N	288	288	288	288

Note: Standard errors in parenthesis. *** for 1% significance, ** for 5% and * for 10%. All lagged variables are lagged only one period. IPO, M&A and total VC for the United States are in US$ million; ag price is nominal soy price in US$/metric tons; oil price is West Texas Intermediate (WTI) - Cushing, Oklahoma, dollars per barrel, annual, not seasonally adjusted, available at FRED. Dependent variable is in US$ million. All regressions include industry fixed effects.

In three of the four models in Table 3 the coefficient on agricultural prices (both contemporaneous and lagged) is negative. However, these coefficients are either not significantly different from zero, or only *weakly* significant at a 10 percent confidence level. The apparently negative effect of oil prices diminishes or disappears when the variable of total VC investments in the United States is added to the model. This later variable captures the effect of overall health

of the VC markets and implies that the greater availability of VC investments is associated with increased investments in startups in agriculture regardless of energy prices[5].

The second set of regressors in Table 3 examine the influence of exits as a signaling mechanism. The results indicate that the higher amounts realized in previous IPO and M&A exits by agricultural technology startups (lagged one year) are associated with higher investments in agtech startups today[6]. IPOs appear to have a stronger effect compared to M&As, but both are statistically significant in some of our models. Both types of exits can be interpreted as playing a role in attracting investments into agtech startups, in line with previous observations in the literature (Gompers and Lerner, 2006; Jeng and Wells, 2000). Additional insights arise from the control variables in Equation (1). It appears that location plays an important role. The estimated coefficient on the U.S. dummy variable is consistently positive and significant throughout these regressions, while the estimated coefficient on the E.U. dummy is consistently negative but only occasionally significant. This corroborates common observations that startups in the United States receive greater VC investments compared to non-US startups. The estimated coefficient on the company age variable indicates the positive effect of age on investments: Companies that have been in the market longer tend to receive greater investments. Results also indicate that larger startups, in terms of number of employees, receive greater investments. These results, all consistent with expectations based on previous studies, suggest that these estimations reasonably reflect the determinants of investments.

Table 4 presents estimation results for investments aggregated at the level of industry or technology categories, as listed in Table 1. At this level of aggregation, more of the variation in investments is accounted for overall, and the coefficients on the independent variables are greater. Results regarding the price effects are much more robust than in the firm-level regressions. Agricultural prices have a significant positive effect on investments overall. Oil prices are negatively related to investments in agriculture, and this relationship persists even when including the variable on total VC investments, which is again found to be positive and significant.

At the industry level of aggregation, we do not have control variables available as in the models with startups—such as age, number of employees, and country. Fixed effects for industry

[5] We also separately estimate adding an interaction between the total VC investments variable and a 2000-2018 dummy, and the resulting coefficient indicates no greater effect during this limited time period

[6] Test regressions find that exits in the same year are not significantly related to investments.

categories are jointly statistically significant. A few of these have larger values including (in this order): (i) Online Services and Content; (ii) Software, Data and IT; (iii) Marketing, Processing and Distribution; and (iv) Agricultural Input Distribution and Sales.

Conclusions

The venture-capital backed startup is a mechanism to contain the financial risks of prospecting and thereby manage the technical and market uncertainties of innovation. The population of such startups developing innovations for agriculture has increased substantially in the last decade, not only in high income countries, but also in emerging and developing countries. Venture investments in such startups has grown as well, reaching 25 to 50 percent of the estimated levels of global private-sector (corporate) agriculture R&D expenditures. This first look has explored several factors likely to have driven this increase in private venture investment in agricultural R&D.

Simple tests of several hypotheses suggest that the positive swings in agricultural commodity prices and successful exits have led to increased investments in agtech startup companies. Especially the runup in agricultural prices after 2000 appears to have had a notable effect on investments. Both contemporaneous and lagged IPO and M&A exits are associated with increased investments at both the firm and industry level. IPOs appear to have a stronger effect on new investments than M&As, even though a much larger share of the returns realized from exits come from M&As. Investments in agricultural startups are to some extent technology specific, favoring online businesses, software, commodity processing, and agricultural input dealers. There is also evidence that startups in the United States receive more venture investments than startups in other countries, all else being equal.

This analysis sheds some light on an important new source of R&D expenditure that has the potential to transform many aspects of private R&D for agriculture, altering the risk profile of innovations being pursued, the human capital networks being accessed, and the market power of companies introducing innovations to the agricultural value chain. Much is needed in the way of further economic analysis of these trends, to improve upon current models, explore additional factors potentially driving such investments (such as public sector research, increased labor costs, or shifts in consumer demand), and the determinants and impacts of different types of exits (with IPOs creating independent competitors but M&As putting new technologies under the

control of industry incumbents). Venture capital has discovered agriculture, but it has only begun to impact agriculture.

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