

# **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. Simple regression 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 by agricultural startups—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-19<sup>th</sup> century. By the mid-20th century, an international agricultural research system, supported and overseen by philanthropic foundations and international organizations, became a major source of new innovations. During the same time frame, large corporate agribusiness and food firms increased their R&D with the objective of increasing profitability of their core 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 primarily consider publicly listed companies that are subject to public disclosure requirements by securities regulators. Such estimates have largely ignored small and medium size enterprises (SMEs) because historically they have contributed very little to industry R&D.

In recent years, however, 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 other 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; Dutia, 2014; 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 in this chapter that until 2006 the amounts invested in agtech startups globally remained relatively negligible, typically less than \$200 million per year, then grew steadily from 2007 to 2012, and then exploded following 2012, exceeding \$3 billion annually in recent years. One industry source claims that venture investments in agricultural technology may have been as high as \$7 billion in 2018 (AgFunder, 2019). At that rate, venture capital and associated private investors could be allocating up to half as much toward agricultural R&D as are the corporate members of the industry.

Yet, these various accounts of R&D investment in agriculture draw upon a range of different private data sources and industry subsector definitions and thus vary in term of how prevalent they find agtech startups to be and how much venture capital they find is being invested in the industry. To some extent, this variation is due to the inherent challenges of industry classifications. Established categories tend to reflect the incumbent structure of industry—such as seeds, agricultural chemicals, or agricultural machinery. However, many of the recent agtech startups span conventional industry categories. For example, a startup may have its primary industry classification in software, yet that software may be highly specialized for data management and decision support of on-farm crop production. One perennial question is the extent to which downstream food manufacturing, wholesale and retail categories should be included, and how, especially since the business models of some of today’s leading startups explicitly seek to shorten or span the entire “farm-to-table” value chain. Variations in accounting of VC investments 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 startup activity and private investment 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). Data sources and procedures for systematic compilation of small-scale private business activity in such countries are nascent, at best. It is not clear why this

surge in venture investment in agricultural technology has occurred in middle- and lower-income countries now or what factors account for this apparent upturn, but it appears to be an important part of this global phenomenon and has remained largely unrecorded.

These startups and their R&D activities can be expected to impact existing agricultural technologies and industry structure. These startups are tapping new sources of financing to support R&D for agriculture. Compared to established R&D organizations, in both the public and private sectors, 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 are even spun off from established R&D organizations to build upon discoveries made within those organization, in order to transfer or translate those discoveries into market applications. Other startups are contributing new research tools or platform technologies—such as novel sensor systems, artificial intelligence algorithms, or genome editing technologies—that could improve the research productivity of all agricultural R&D organizations, public and private. Yet, other startups may be directly competing with established public-sector or corporate R&D agendas, seeking to “disrupt” current technologies or ways of doing business.

The VC-backed startup is effectively a mechanism to contain the financial risks of prospecting in the process of R&D, reducing or managing the technical and market uncertainties of innovation. While many startups fail in the attempt, some do prevail in bringing their innovation to market. An increase in the rate of successful startups may help to counter recent trends of increased market concentration in agribusiness, in which fewer larger firms have been 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, market concentration can lead to exploitative monopolies, but with innovation, new competition can erode monopoly power.

This chapter investigates the increase in the number of new agricultural technology startups globally. What are the dynamics of entry and growth of new firms financed by venture capital? Where is it occurring? To what extent are they concentrated in high income countries? And what are the main market categories or technologies they are pursuing?

This chapter also explores a range of economic factors and circumstances that might help explain this growth of 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 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 both enjoyed exponential growth and 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 virtuous cycle. The fundamental question is the extent to which the R&D and innovation system of agriculture is being transformed by this influx of equity-based private investments in R&D-intensive startup companies and whether it will come to operate more like these other high-tech industries in the long run.

To investigate these changes, we compile a global dataset of 4,552 companies in agriculture, founded from 1977 to 2017, with 11,998 associated financial transactions, including investments into and exits from these startups. The lack of reporting requirements for privately held firms generally make it a challenge to systematically track startups and their financing (Cumming & Johan, 2017). To overcome this challenge, we draw primarily from the commercial data vendor PitchBook (by Morningstar) and augment its data with additional company and financial transaction records from competing commercial data sources, VentureSource (by DowJones) and Crunchbase (founded by TechCruch). The financial transactions reported include a range of venture capital, seed, and angel investments, some other private equity deals, as well as debt financing. They also include transactions by which early investors and founders exit their investments in these startups, such as initial public offerings (IPOs), mergers and acquisitions (M&As), as well as other types of buyouts. While the transactions data do indicate some bankruptcies and closures of the startup firms, the reporting of these is incomplete, and so we are left to impute a rate of firm closures based on clues in the data. Together, these data allow us to explore the startup life cycles and exit outcomes over time and across the full range of different technologies being developed (e.g. biotech vs software), across the full range of subsectors of agriculture (e.g. inputs vs. outputs, or crops vs. livestock), and across the globe.

Our data summaries show an exponential growth in the number of the startups from about 2006 to the present. The largest share of startups is in the United States (33 percent), followed by

Europe (23 percent), with the remainder (44 percent) 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 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 final third encompass a wide range of other technologies, applications, and business models, including marketing and sales, financial and business services, and even on-farm production.

Investments into these startups over the entire period is US\$22.1 billion. Annual investments were muted historically but exhibit a sharp increase around 2012 and reach an annual maximum of US\$3.2 billion in 2017. About two thirds of the investment amount is in the form of early and late stage venture capital with debt financing also important. About 10 percent of startups in the sample exit via IPO. In contrast

This chapter proceeds as follows. We turn next to a quick overview of the economic literatures on agricultural R&D and on venture capital. We then introduce a new data set on agricultural technology startups. The full sample of startups is used to track overall trends, such as founding rates, the geography of startup globally, and startups by technology or industry categories. A narrower subset of startups that also have data on their investments is used to analyze growth in investments and factors associated with that growth, both at the firm level and at the industry level. Results suggest that recent surges in commodity prices, together with higher amounts of venture capital being invested overall, facilitated by signals from successful exits by prominent startups in agriculture, may have led to the surge in venture capital investments in agriculture. We conclude that the

## **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 globally 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 the share conducted by the public sector down slightly to approximately 60 percent and the share conducted by the private sector up to approximately 40 percent (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. 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 argue 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 costs. The timing of an investment is thus 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 can be applied 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 startups, 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 especially 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. In examining economic determinants of venture capital funding, Groh and Wallmeroth (2016) and Jeng and Wells (2000) investigate both developed countries and emerging markets. Groh and Wallmeroth (2016) show that the global share of venture capital investments in emerging markets increased from 2.4 percent in 2000 to 20.8 percent in 2013, indicating that the salient factors for VC investors are increasingly found in emerging markets.

Gompers and Lerner (2004) point out the greater number of rounds and larger amounts of VC investments go into high-tech industries, such as computers and biotechnology, compared to other more traditional industries. Puri and Zarutskie (2012) compare VC and non-VC-financed firms and find that the key firm characteristic that attracts VC investment is its potential for scale. Even though agriculture, broadly speaking, may be considered a traditional industry with low margins, most VC investments in the sector are targeting the application of high technologies, such as geospatial technologies, digital sensors, robotics, biotechnology, automated 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 can 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 biotech investments, with potential market uptake depending on whether other countries will follow the European or the American regulatory standards for this technology (Rausser et al., 2015).

### *Venture Capital Exits*

There is a growing 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 exits (Jeng and Wells, 2000) and M&A exits (Felix et al., 2013; Groh and Wallmeroth, 2016) on subsequent VC investments in earlier stage startups. 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 were widely publicized and may have stimulated subsequent investments by VCs in other agricultural technology startups.

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 shows that such variables can in turn determine the exit outcome, finding, for example, that startup size is related to chance of exit while industry growth rate is not. Puri and Zarutskie's (2012) comparison of VC-backed and non-VC-backed companies , find evidence that companies with VC investors have a higher likelihood of resulting in an M&A or IPO exit and lower likelihood of a failed exit, controlling for industry-specific characteristics and year fixed effects. Gompers and Lerner (2004) have extensive discussions on the likelihood of startups going public via IPO, and they show that generally better industry conditions, such as captured in an industry equity index (e.g. biotechnology index), are positively associated with that industry's number of IPOs.

Previous and contemporaneous exit outcomes, even in emerging and developing economies, are found to be directly associated to VC investments. While Groh and Wallmeroth (2016) find evidence that M&A exits impact venture capital funding positively, Jeng and Wells (2000) find that IPOs play a greater role on determining venture capital investments in the later stages of the startup lifecycle. 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 observations that overall agricultural R&D activities have shifted toward emerging markets, makes it reasonable to expect that the share of VC investments in agriculture has shifted towards emerging markets as well.

### *Venture Capital and Innovation*

Following results by Kortum and Lerner (2000) that suggest VC dollars may be three times as productive as corporate R&D dollars in generating patents, a number of studies have examined

the relationship between VC and innovation. The hypothesis that VC-backed firms are more innovative is consistent with more general observations that VC investors select firms that are more likely to succeed and to do so at scale (Baum and Silverman, 2004; Engel and Keilbach, 2007; Puri and Zarutskie, 2012), but there is also evidence that VC investors encourage companies in which they invest to enhance their knowledge absorption and R&D capacity (Da Rin and Penas, 2007). There is evidence that startups receiving VC investments file more patent applications both in the short run and more permanently, and moreover those patent applications are more likely to be successful, an indication of higher quality innovation (Arqué-Castells, 2012).

Even amongst VC-backed startups there may be incentives to become more innovative. Nadeau (2011) finds that VC-backed startups that exit via the more-profitable IPO route are more likely to be engaged in patenting than those that exit via M&A, at least in key sectors such as biotechnology, IT, and internet services. Gaule (2018) similarly finds that VC-backed startups with higher quality patents, are more likely to be successful, exiting via an IPO or a highly valued M&A.

One question that arises is the extent to which private equity or venture capital investment into startup companies can be compared to or even or proxy for R&D expenditures. Kortum and Lerner (2000) and Metrick (2007) distinguish between R&D financed by corporations and R&D financed by venture capital. However, publicly traded corporations report R&D expenditures according to established definitions, while small privately held firms do not. Kortum and Lerner assume that the bulk of venture financing goes to support innovative activities while acknowledging that some VC investments may be made in low technology startups or may be spent on other activities such as marketing. Whether these exceptions are greater in agriculture than in industries that have traditionally received VC investment is an important but ultimately empirical question.

## **Data on Venture Capital Investments in Agriculture**

The data for this first look at venture capital investment in agriculture is drawn from several commercial data sources and consists of information on 4,552 startup companies and 7,596 financing deals. We follow the approach of Hall and Woodward (2010) to compile a dataset drawn from a variety of data sources in order to overcome the limitations of data

reporting and potential biases of any one data source. Of the sources we draw on, the industry standard is generally regarded to be PitchBook, a financial database focused on venture capital and private equity investing, owned by MorningStar. Data from PitchBook is then augmented with data from two other sources: VentureSource and Crunchbase. From each source, two types of data are available, linked in a one-to-many relationship: data on companies and data on financing deals of those companies.

A comparison of company data listings across these three data sources was undertaken with an expectation that overlap among data sources would allow for cross-validation of firms and their deals. However, as Figure 1 illustrates, we find minimal overlap across data sources of company listings. Our initial sampling, drawn from PitchBook, included 2,005 companies founded in the 40 years from 1977 to 2017, along with 3,667 financial deals for those companies, as designated by PitchBook’s “AgTech vertical” industry category.<sup>1</sup> From VentureSource, by DowJones, we drew an additional 680 companies with 1,759 associated deals—identified by VentureSource’s “Agriculture and Forestry” industry category<sup>2</sup>—that were not found in the PitchBook data. From Crunchbase—identified by their “Agriculture and Farming” industry group<sup>3</sup>—we drew an additional 1,885 companies beyond those listed in either PitchBook or VentureSource and 2,170 associated deals for those companies. Just 557 (12 percent) of the total companies were found in more than one data source, and only 90 (2 percent) of the total companies identified were listed in all three data sources.<sup>4</sup> This pattern of data availability suggests that any analysis based upon one primary data source (such as AgFunder, 2015, 2019;

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<sup>1</sup> 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)

<sup>2</sup> VentureSource’s “Agriculture and Forestry” industry category is a subset within its larger category of “Industrial goods and materials”

<sup>3</sup> Crunchbase’s “Agriculture and Farming” industry group includes companies in Agriculture, AgTech, Animal Feed, Aquaculture, Equestrian, Farming, Forestry, Horticulture, Hydroponics, and Livestock.

<sup>4</sup> For those 12 percent listed in more than one data source, for each company we use only data from one data source, depending upon availability, in the following order of preference: (1) PitchBook, (2) VentureSource, (3) Crunchbase. See numbers of companies and deals in Figure 1.

CBInsights; Finistere; KPMG; etc) provides a limited and largely separate sampling of overall venture investments in the industry, relative to analyses based on other data sources.

Of the total 4,552 unique companies and 7,596 unique deals, we take about half of the data records on companies and deals in our collection from PitchBook, and the other half from VentureSource and Crunchbase (Figure 1). Of these data sources, PitchBook had the most complete data overall, VentureSource was more complete in reporting older companies and deals, and Crunchbase was helpful in identifying a wider range of startups companies internationally, but unfortunately was not able to provide as much coverage of deal information for those 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 data, 1,366 (29 percent of the total) report at least one deal in which the amount is disclosed (others report deals that occurred, but do not disclose amounts) and 1,092 (24 percent) report an identified exit deal.

Given these discrepancies in the availability of deal information, the subsequent analysis is undertaken 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 those factors that may be associated with the recent growth in those investments. Arguably, given the skewed nature of valuations and investments in venture capital markets generally, together with a propensity to report information on larger, more significant investments and exits (Hall and Woodward, 2012), it stands to reason that the 29 percent of companies with disclosed deals represents a considerably greater share of the overall financing activity in the industry. It is important to emphasize that, despite efforts to be inclusive, this dataset is still necessarily an underrepresentation of overall activity in the industry. Yet, the following analyses are based on a broad, representative sampling of private investment activity across agriculture globally.

#### *Full combined data set of startup companies in agriculture: global summary statistics*

For many of the 4,552 companies in the combined sample, founding date is available. For those companies with founding date missing but for which deal information is available, we use the date of the first deal as a proxy for the start year. Figure 2 plots the number of startups by founding year.

Qualitatively, there appears to have been three phases of growth in agricultural startups. First, from 1977 to 1991 we see steady, slow growth, with between 20 to 50 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 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.<sup>5</sup>

The overall sample of 4,552 companies also includes data on physical address, which enables analysis of the geographical distribution of entrepreneurship in agriculture 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 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 startups in the sample, led by Brazil with 88. Agricultural startups are also found in Africa, with the most in South Africa (41), followed by Kenya (31) and Nigeria (27). The pattern of VC-funded startups follows the growth pattern of VC in developing countries identified by Groh and Wallmeroth (2016). This global distribution of 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

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<sup>5</sup> 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.

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, Dutia, 2014, and AgFunder, 2019), as detailed in the Appendix.

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 in Table 1: 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.<sup>6</sup>

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. Of these the two largest 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: investments and exits*

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). However, of these reported deals, many do not disclose the amount of the deal.

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<sup>6</sup> For example, under the International Patent Classification (IPC) system, multiple patent classifications can be assigned to a single patent.

To analyze venture capital investment trends, we narrow to a sub-sample of just those 1,367 startups (29 percent of the overall sample) that report at least one venture-type money-in investment with a disclosed amount. In other words, 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, as well as any other private equity investments. Companies that did not report deal amounts and companies with only private equity investments or debt financing were dropped from the sample for this part of the analysis. Figure 3 displays the total money in investments by type and year for those firms from 1977 to 2017.

Total money-in investments over the entire period was US\$22.1 billion. Following a sharp increase after 2009 in new startups overall (see Figure 2), investments exhibited a sharp increase starting in 2011 and reach an annual maximum of US\$3.2 billion in 2017 (Figure 4). We can be confident that this maximum would be exceeded in 2018, were these data not truncated, as industry reports indicate investments in 2018 significantly exceeded those in 2017 (AgFunder, 2019). Early and late stage venture capital (totaling US\$8.1 and US\$8.4 billion, respectively) represents most of the money raised by these startups. Even though absolute amounts increased substantially over time, the composition of investments between early-stage and late-stage VC remained quite stable. Debt financing of these firms totaled US\$4.2 billion, but appears more sporadic, coming in large tranches when it does occur.

The ultimate fates of the 1,584 startup companies with any associated data on transactions can be roughly divided into three types of outcomes. First, some startups go through a successful financial exit. In that transaction, the initial venture investors are able to exit their ownership of otherwise illiquid equity shares and realize a return on their investment. Successful exits include initial public offerings (IPOs), mergers or acquisitions by other companies (M&As), as well as other less common buyouts, such as management buyouts or private equity buyouts. Second, the fate of startups that are not successful is closure of the company—with some filing for bankruptcy, some liquidating assets, and some just quietly winding down operations until effectively defunct. The third fate, if neither of the other two has occurred, is for a startup to be remaining in business as a privately held company.

Cumulatively, for the 1,584 startups for which we have transaction data, we find that 150 (9.5 percent) exited via IPO, 739 (46.7 percent) exited via M&A, and 159 (10.0 percent) exited via some other buyout. Interesting, just 49 of the startups (3.1 percent) reported closure or

bankruptcy, implying that 487 (30.1 percent) are still in business. Not only does this ratio seem unrealistic, but others have identified a strong bias against negative news, including firm closures, small investments, and other indicators of underperformance, in venture capital data sets such as these (Hall and Woodward, 2012). We find that of the 49 startups that do report closures, 90 percent of these closed within four years after their last money-in deal. It stands to reason that companies relying on venture capital need to raise new money every two to four years, and if they stop doing so, it is a strong indication that they have closed. Given that many of the 487 (30.1 percent) startups deemed “still in business” had fallen silent, lacking any newly announced deals for more than four years, we estimate that 417 (26.3 percent) face a similar probability of having closed and, thus, just 70 (4.4 percent) of the total sample were likely still in business.

Looking at exits and closures over time (Figure 7.a), we see that they occurred only sporadically prior to the mid-2000s. The number of exits began to grow steadily after 2005 and peaked in 2015. The numbers of closures (reported and estimated) began to increase about five years later, around 2010. Exit amounts are much more sporadic and took off dramatically in 2008 when over \$2.3 billion was realized by investors (Figure 7.b). The maximum year for exit amounts was 2013, at close to US\$6 billion, mostly due to M&As. While the counts of exits (Figure 7.a) have displayed a smoother year-on-year growth trend, the sporadic nature of the values of exits (Figure 7.b) belies the tendency for exit valuations of startups in VC portfolios to be highly skewed, which has been generally observed in venture investing for decades (Gompers and Lerner, 2004; Metrick, 2007).

### **Analysis of factors associated with increased venture capital investments in agriculture**

There are a number of 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 across the industry pushed potential returns 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). While certainly logical, agricultural commodity prices alone do not seem sufficient to explain why venture capital investments began to flow into agriculture.

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. And the timing of those shifts may also have played a role. “Cleantech” investment funds—which had focused primarily in the energy sector, presumably encouraged by high energy prices—may have discovered agriculture when investing in biofuels. Crude oil prices faced a sharp increase in 2007 and 2008, followed by a sharp downturn in 2009, and while oil rebounded and remained around US\$100/barrel from 2011 through 2014, it fell back to less than US\$50/barrel within a year (Figure 5.b). At key points when oil prices dropped, investors in clean-tech may have pivoted toward opportunities in agriculture as agricultural commodity prices remained higher. While such conditions seem to have held for only short windows of time (comparing Figures 5.a and 5.b) the swings in price ratios may have been dramatic and long enough at least for venture investors to have “discovered” the agricultural sector. Once discovered, agriculture continued to be a focus of investor attention.

There is also very likely a supply side factor, given that overall VC investments in the economy increased steadily during this period. Ewens, Nanda, and Rhodes-Kropf (2018) document an increase in investment volume by existing VC firms as well as growth in new financial intermediaries after 2006. Figure 6 shows that growth in investment in agtech appears correlated with total VC investment in the United States (as according to PWC, 2019). Thus, an additional hypothesis is that a greater supply of VC coupled with 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).

Finally, it is reasonable to expect that market signals from successful exits may have played a role. The most desired outcomes for VC investors are an IPO or an acquisition (M&A), as these 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 VC investments.

Anecdotally, there were several large exits from agricultural startups 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. According to the data, a regular rhythm of IPOs and M&As began in 2006, with significant returns first logged in 2008 (Figure 7.a and 7.b) coinciding with the sharp increase in the numbers of new startups (Figure 2) and investments (Figure 4). In agriculture, it appears that M&As have generated much larger gross 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 on venture investments in the agriculture, thus helping to attract new investors and investments in the newer startups in agriculture.

#### *Regression analysis of investments made at a company level*

A regression analysis was undertaken to offer more systematic description of the relationships between venture capital investments in agricultural startups and several of these factors hypothesized to influence decisions by venture capitalists to invest. A simple framework used for analysis at the firm level is described 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,  $y_{it}$ , is the sum of *reported amounts of* investments received by a startup  $i$  in year  $t$ . If a startup did not exist in year  $t$ , the observation is dropped. If a startup did exist in year  $t$  but simply received no investment, the observation is kept and  $y_{it}=0$ . If a startup received more than one investment in a given year, then those investments are summed.

Of the independent variables in Equation (1), the  $P_{1,t-k}$  are agricultural commodity prices, lagged  $k$  years, for which World Bank and FAO agricultural commodity price indices as well as nominal soybean prices are considered. We also focus analysis on possible changes in the relationship with agricultural commodity prices in the period after 2000, when they began to grow and became more volatile, by interacting ag prices with a date range dummy variable. The  $P_{2t}$  are nominal oil prices. The  $VC_t$  are total annual venture capital investments in the United States, according to PwC. The exit variables,  $ee_{t-k}^{m\&a}$  and  $ee_{t-k}^{ipo}$  measure the annual sum of money raised in IPO and M&A exits of the agricultural startups in the sample,  $k$  years prior to year  $t$ . The  $X_i$  are control variables. The sample is very heterogenous, including firms in different stages of the startup lifecycle, in different countries, and in different industry categories. Company age is used to control for stage in the startup lifecycle. Dummy variables are added for

startup locations in the United States and in Europe. And dummy variables are added for the 12 industry categories described in Table 1. Finally,  $u_{it}$  is the random error term clustered at the firm level.

Since data for the independent variables of oil prices and total VC investments were available only after 1995, the sample incorporates investment activity from 1995 to 2017. We build an unbalanced panel that consists of 12,094 observations involving 1,447 startups. Most of the firms were founded after 1995, with the frequency of firms entering the dataset increasing toward the end of the period, according to the trend illustrated in Figure 2. We have 2,439 firm-year observations with positive investment values and 9,655 with zero values. Due to this censoring from below, we use a tobit regression model.

We are not attempting to deal here with several important econometric challenges in working with these data. First, we are not dealing with unreported data, at two levels, in the dependent variable: for many startups we observe that investments occurred but their value is not reported, which therefore gets represented as a zero value; but we also know that there are many more investments that are entirely unreported. Second, we are not dealing with the unbalanced nature of the panel. And third, we are not attempting to deal with the endogeneity or the dynamic nature of these investments. Clearly, the trends we have summarized in the previous section are all largely moving in the same direction, making identification problematic, yet beyond the scope of this chapter's objective as a descriptive exercise.

Table 2 presents results for the firm level regression described by Equation (1). The estimation results corroborate observations from the summary statistics displayed in Figure 5.a that trends in agricultural commodity prices are positively associated with trends in investments in agtech startups. The result that investments are more strongly associated with agricultural commodity prices after 2000 are consistent with the notion that growing commodity prices could have shifted attention of venture capital investors towards agricultural markets.<sup>7</sup> Oil prices, in contrast, are negatively related to investments. This may be picking up the trends visible in Figure 5.b that investments initially remained low as oil prices increased and then later boomed as oil prices fell.<sup>8</sup>

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<sup>7</sup> Estimation results were found to be robust across various versions of the model that used different prices and lags, not reported here.

<sup>8</sup> In addition, we tested the effect of the ratio of agricultural commodity prices to oil prices in regressions not reported here, with a larger ratio indicating a potentially greater return in agriculture compared to energy. We find a

The variable of total VC investments in the United States reflects the overall health of VC markets and implies a greater availability of VC investments which is plausibly associated with increased investments in startups in agriculture all else being equal.<sup>9</sup>

Coefficients on the agIPO and agM&A variables indicate that the higher amounts realized in the previous year's exits by agricultural technology startups are positively associated with higher investments in agtech startups in a current year.<sup>10</sup> IPOs appear to be more strongly associated than are M&As, but both are statistically significant in this regression. Both types of exits could be interpreted as playing a role in signalling returns and attracting investments into agriculture, in line with previous observations in the literature (Gompers and Lerner, 2004; Jeng and Wells, 2000).

Additional insights arise from the control variables in Equation (1) and Table 2. It appears that location is an important differentiator. Even though similar numbers of startups are found in the United States and Europe (Figure 3.b), the estimated coefficient on the U.S. dummy variable is strongly positive and significant, while the estimated coefficient on the European dummy variable is negative and significant. This corroborates common observations that VC finance is more mature and active in the United States, and generally U.S. startups tend to receive greater VC investments compared to non-U.S. startups. The estimated coefficient on the company age variable would be expected to be positive, to indicate a positive relationship between age and investments: Companies that have been in the market longer and grown larger tend to receive larger VC investments, which is by design in most VC investment strategies (Gompers and Lerner, 2004; Metrick, 2007). The negative coefficient on company age likely reflects a high frequency of zero annual investments for older startups. This could arise because we still give four years of zero investments after the last reported investment to those companies that we estimate are ultimately closed; perhaps this is too generous, if many of these companies in fact closed sooner (and thus those observations should have been dropped rather than assigned a  $y_{it}=0$ ). Coefficients on industry category dummies are positive and significant (in order of magnitude) for (i) Biotechnology, genetics, and health, (ii) Chemicals, and (iii) Software, data

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strong positive effect of the price ratio on the size of investments when limited to the 2000-2017 window. The coefficient on the price ratio over the entire timeframe is, however, not significant.

<sup>9</sup> We also separately added an interaction between the total VC investments variable and a 2000-2018 dummy, but the resulting coefficient indicates no stronger relationship during this more limited period.

<sup>10</sup> Test regressions find that exits in the same year are not significantly related to investments.

and IT, indicating relatively more and/or larger investments are received by companies in these categories.

*Regression analysis of investments made at an industry level*

To explore venture investments made at the level of the industry categories described in Table 1 (and detailed in the appendix), a similar model is estimated:

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

where the dependent variable, now, is  $y_{ct}$ , the annual sum of investments for all startups in industry category  $c$  during year  $t$ . There are reasons to believe that factors affecting investment may vary across industry or technology. As already noted, about a quarter of the startups in the sample are categorized in more than one industry category, due to the multidisciplinary nature of the technologies being developed or due to integration across markets. We therefore split these 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  $t$ ). The independent variables are the same as defined for Equation (1).

We build a balanced panel of 12 industry categories over 24 years from 1995 to 2018 to estimate a fixed effects model also using a tobit regression model. Table 3 presents estimation results for investments aggregated by industry category. At this level of aggregation coefficients on the independent variables are naturally greater than in the firm level analysis. Agricultural commodity prices, at least after 2000, exhibit a significant positive coefficient. Oil prices are again negatively related to investments in agricultural startups. Coefficients on the agIPO and agM&A variables are again positive and significant, with the magnitude of the IPO coefficient again larger than the M&A coefficient. The variable for total annual VC investments is positively and significantly related to VC investments in agriculture.

At the industry level of aggregation, not all of the control variables used in the firm level analysis—such as age or location—are meaningful. Fixed effects for industry categories are jointly statistically significant. A few of these have larger values including (in order): (i) Online services and content; (ii) Software, data and IT; (iii) Marketing, processing and distribution; and

(iv) Agricultural input distribution and sales, indicating relatively more frequent and/or larger aggregate investments are received in these categories.

## **Summary and 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 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, almost half as much as the estimated amounts of global corporate agriculture R&D expenditures. This first look has introduced extensive representative data on startup companies related to agriculture and their financial transactions, and it has explored several factors likely to have driven the observed increase in private venture investment in agricultural R&D.

Simple tests of several hypotheses suggest that agricultural commodity prices and successful exits have been closely associated with increased venture capital investments in agriculture. Especially the runup in agricultural commodity prices after 2000 appears correlated with investment levels. Both IPO and M&A exit amounts realized by agricultural startups are associated with subsequent investments at both the firm and industry levels. IPOs appear to have a stronger relationship with new investments than do 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 biotech, 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 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 networks of highly skilled human capital being accessed, and the market power of companies introducing innovations throughout the agricultural value chain. Much is needed in the way of further economic analysis of these trends, to improve upon current models, explore factors potentially driving such investments (such as public sector research, other sources of technological opportunity, 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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Figure 1. Venn diagram of data accessed on new startups in agriculture and their financial deals, by data source: our primary data source is PitchBook, augmented by additional company and financial deal records from VentureSource, and then Crunchbase; data for just 12 percent of total startups was found to be available from more than one source

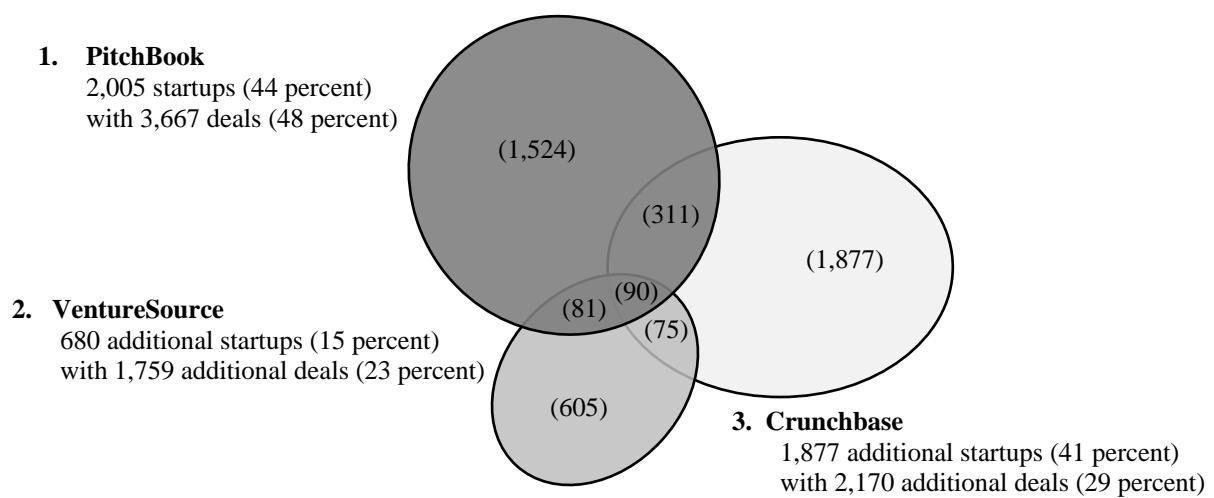


Figure 2. Venture-capital funded startups in agriculture by founding year, 1977-2017

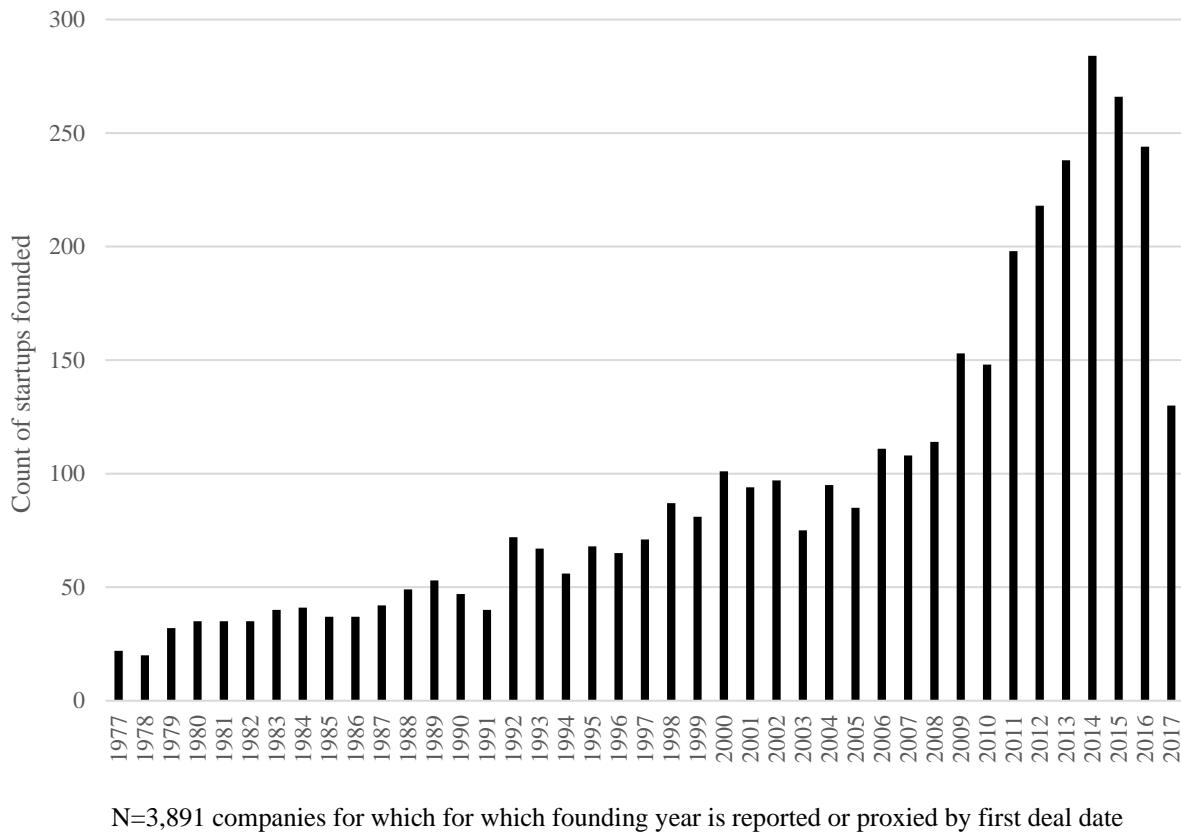


Figure 3. The global scope of new venture-capital funded startups in agriculture, 1977-2018: (a) global density mapping, by city and/or postal code, and (b) global share, by country and region

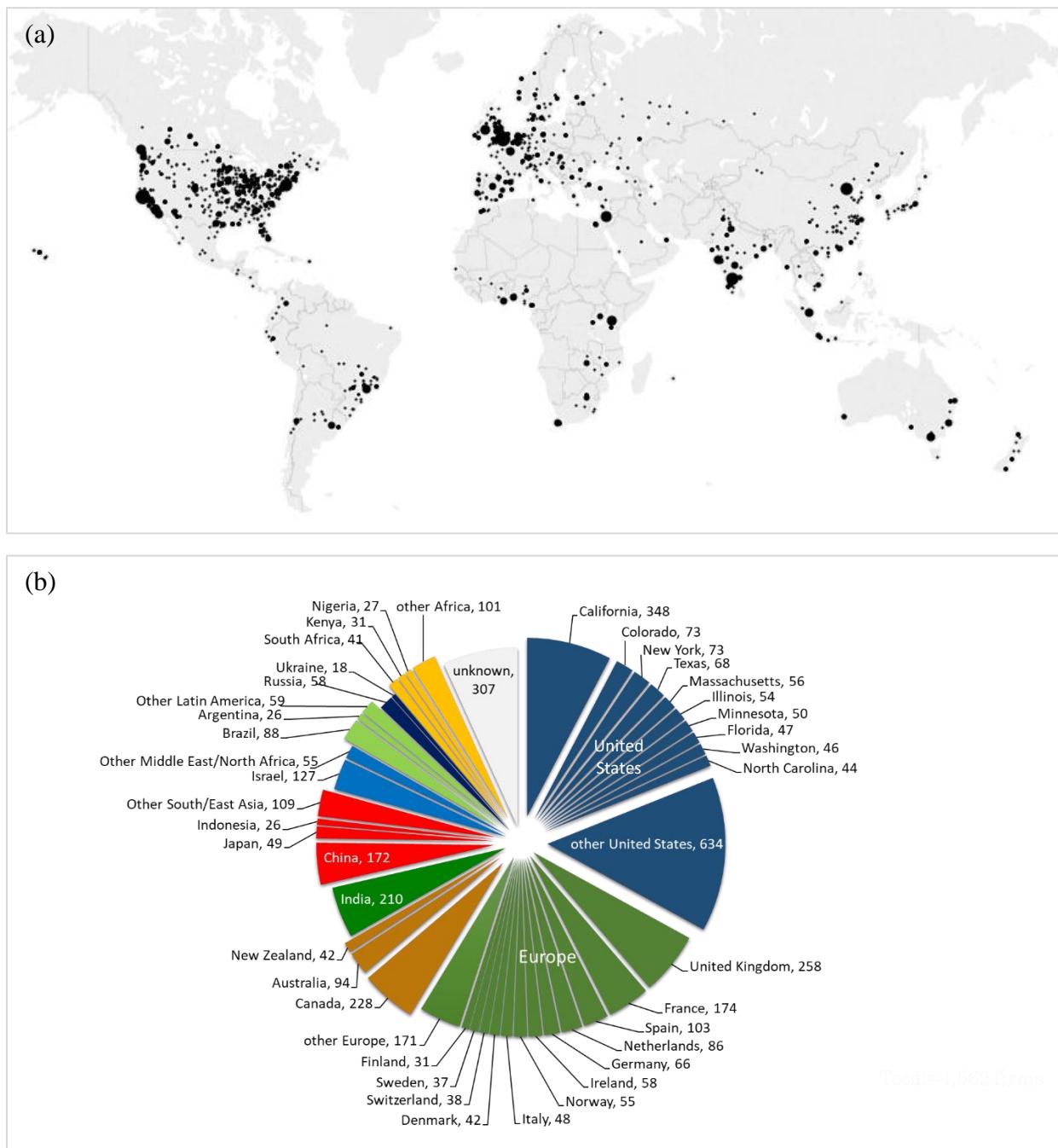


Figure 4. Investments into venture-capital funded startups in agriculture, 1977 to 2017, by type of investment

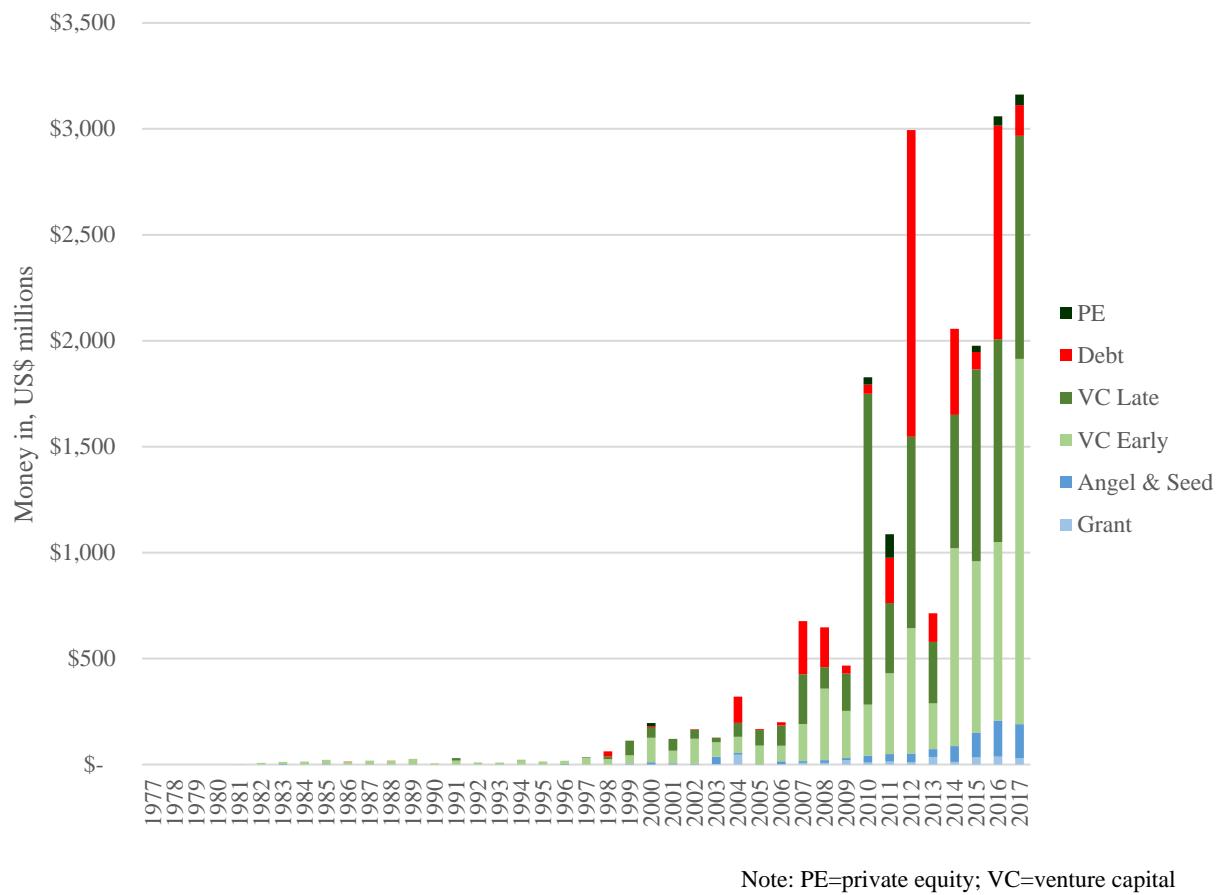
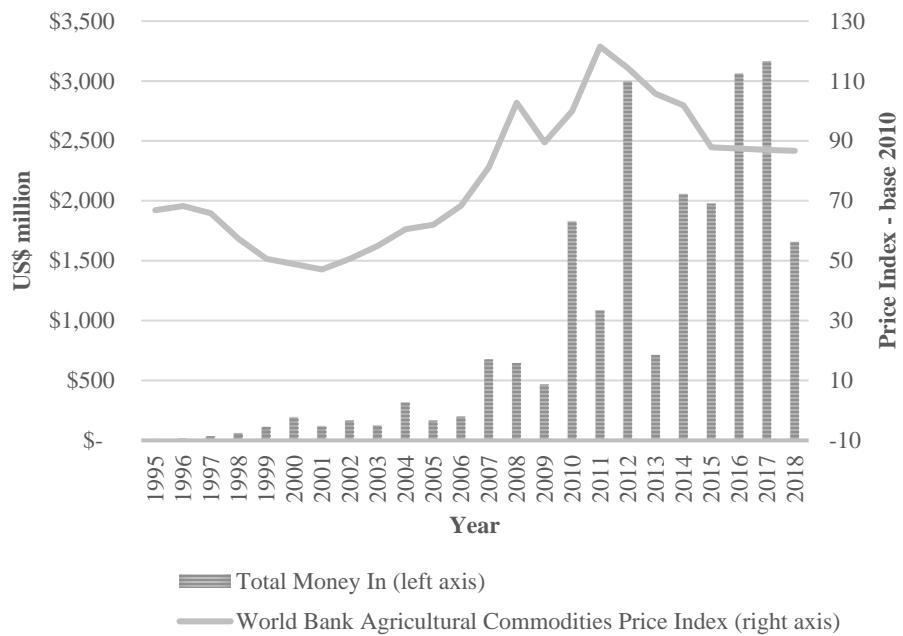


Figure 5. Investments in agricultural technology startups plotted against:

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



(b) oil prices (US\$/barrel)

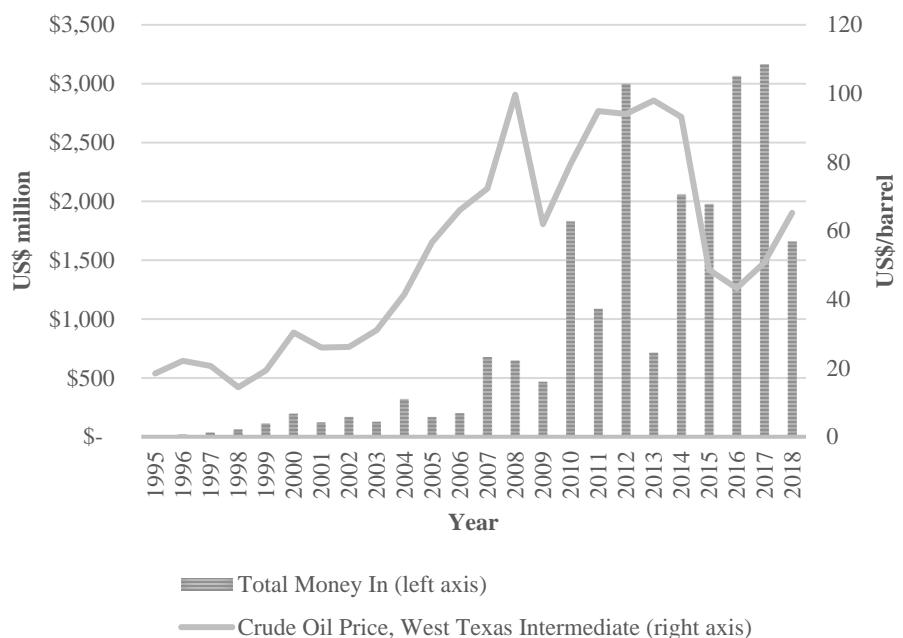


Figure 6. Investments in agricultural technology startups plotted against total annual VC investments in the United States

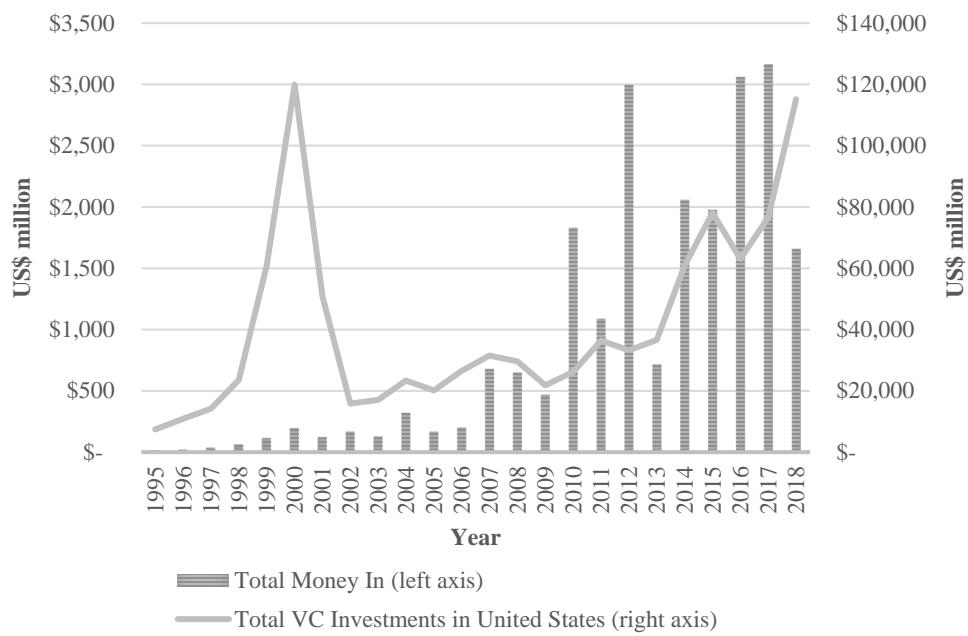
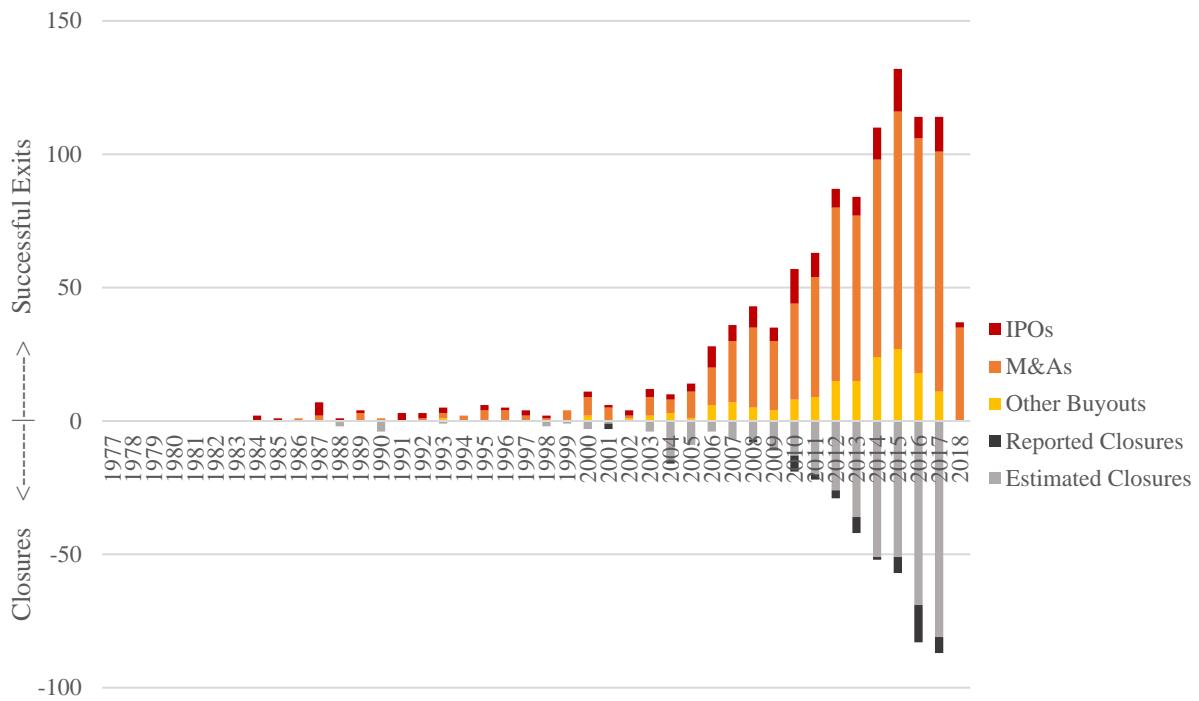


Figure 7. Exits by venture capital investors from startups in agriculture

(a) Counts of successful exits and closures for the 1,584 startups with associated deals data, 1977-2018



(b) Amounts realized from successful exits, 1977-2018

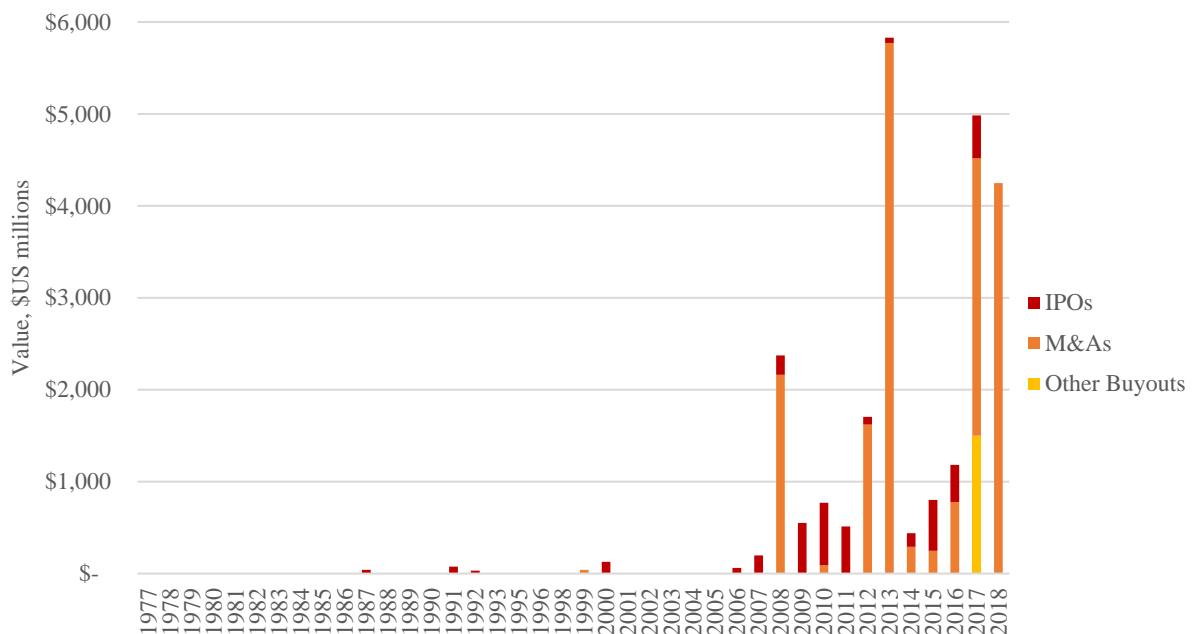


Table 1. Industry and technology categories characterizing venture-funded startups in agriculture

Category*	Number of startups with activities described by each category
Agricultural input technologies or services	2,482
Software, data, and information technologies	942
Devices or sensors (electronic hardware)	430
Genetics, breeding, biotech, or health	918
Chemicals	230
Equipment or machinery (mechanical hardware)	302
Ag input distributors, dealers, or co-operatives	678
Ag producers or farms	467
Marketing, processing, manufacturing (including animal feed)	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 (27 percent) are identified with two or more categories

Table 2. Firm level tobit regression of commodity prices, lagged exits, and total VC supply on investments made in existing firms annually over the period 1995-2017

Independent Variables:	Dependent variable:
	Amount invested in firm $i$ in year $t$
Ag commodity prices	0.01170 (0.02122)
Ag commodity prices after 2000	0.08949*** (0.02211)
Oil prices	-0.31869*** (0.08935)
Ag IPO amounts, lagged 1 year	0.01204*** (0.00443)
Ag M&A amounts, lagged 1 year	0.00179*** (0.00049)
Total VC invested in US	0.00026*** (0.00005)
Firm age	-0.88796*** (0.18550)
EU dummy	-1.99442 (1.32819)
US dummy	9.52096*** (2.35058)
Industry category dummies	
Constant	-85.62672*** (18.55865)
Observations	12,094

**Notes:** Standard errors in parenthesis. \*\*\* for 1% significance, \*\* for 5% and \* for 10%. All lagged variables are lagged only one period. IPOs and M&A values for agriculture and Total VC for the United States are in US\$ million; Ag commodity price is the nominal US soy price in US\$/metric tons; oil price is West Texas Intermediate (WTI) Cushing, Oklahoma, US\$ per barrel, annual, not seasonally adjusted available at FRED. Dependent variable of annual firm deals value is in US\$ million.

Table 3. Industry level tobit regression of commodity prices, lagged exits, and total VC supply on investments made in 12 industry categories annually over the period 1995-2017

Independent Variables:	Dependent variable:
	Amount invested in industry category $j$ in year $t$
	0.29046
Ag commodity prices	(0.25682)
	0.49434**
Ag commodity prices after 2000	(0.22219)
	-2.72660
Oil prices	(1.73527)
	0.18959***
Ag IPO amounts, lagged 1 year	(0.06578)
	0.01305*
Ag M&A amounts, lagged 1 year	(0.00693)
	0.00085**
Total VC invested in US	(0.00040)
Industry category dummies	
Constant	-372.03315*** (103.07161)
Observations	288

**Notes:** Standard errors in parenthesis. \*\*\* for 1% significance, \*\* for 5% and \* for 10%. All lagged variables are lagged only one period. IPO and M&A values for agriculture and Total VC for the United States are in US\$ million; Ag commodity price is the nominal US soy price in US\$/metric tons; oil price is West Texas Intermediate (WTI) Cushing, Oklahoma, US\$ per barrel, annual, not seasonally adjusted available at FRED. Dependent variable of annual firm deals value is in US\$ million.

## **Appendix. Characterization of agricultural startup firms by industry and technology**

In the data obtained from commercial vendors, startup companies either self-report or the commercial data vendor composes a business description, usually a short paragraph, and assigns an industry code or segment categorization. These vary, however, across data vendors. In order to ascertain more uniformly the industry or technology in which startups are engaged, we queried and filtered the company description and industry categorization fields to assign startups to twelve categories, as summarized in Table 1. These categories are relied upon to introduce field-specific controls in our estimations (Tables 2 and 3). The following notes describe in greater detail the types of businesses that are included in each of the categories.

### *Business and financial services*

1. Real estate; Land brokerages
2. Human resource management, Labor contracting, Training and education services
3. Financial services; investment
4. Insurance; risk management
5. Industry associations and advocacy
6. Economic development and regional development organizations
7. “B2B” services or marketplaces (in combination with the “Online” category)
8. Publishing, catalogues, information for industry clients (may be in combination with “Online” category)
9. Consulting and advisory services
10. Contract research services

### *Online services and content*

1. “Online,” “website,” “web,” or “portal”; often “platform”
2. “B2B” or “B2C”, but almost always in combination with another appropriate category
3. “Apps” or “mobile”, often in combination with “Software, data, and IT” category

### *Biotech, genetics, and health*

1. Companies described as “biotech”

2. Companies that mention “genetics”
3. Breeding
4. Biological control
5. Biopesticides
6. Biofertilizers, compost, biochar, other biologically derived soil amendments
7. Microbial/microbiome
8. Animal health, including vaccines (but NOT feed additives)
9. Animal reproduction, such as sexing, artificial insemination

*Chemicals*

1. (Agro- or Ag-) chemical manufacturing
2. Any of the “-icides”, if not explicitly biological (i.e. not “biopesticides” or not if explicitly described as a protein or peptide, etc., which were instead included in “Biotech, genetics, and health” category)
3. Mention of a specific class of chemical compounds that characterize the company’s products
4. Inert materials with beneficial properties as soil additives, fillers, growth media, weed block, mulches, etc
5. Nanomaterials
6. NOTE: use of this category indicates R&D or manufacturing, not merely distribution or “provider” of chemical products

*Electronic devices, sensors, systems*

1. Mention of “device”, “sensor”, smart or automated systems, measurement or monitoring in electronics context
2. “hardware” (as opposed to “software”)
3. Robots, drones, unmanned or autonomous vehicles (UAVs)
4. Lighting or LED systems for contained or indoor agriculture
5. Control systems
6. Note: technologies/products that would be in “electrical engineering”, not “mechanical” “civil” or “hydrological” engineering (these are under “Machinery/Equipment” category)

*Software, data, and IT*

1. “Software” or “App”
2. “Data”
3. “Analytics”
4. “Artificial intelligence” or “Machine Learning”
5. “Blockchain” or “Distributed Ledger”

*Machinery and equipment*

1. Manufacture of farm machinery or equipment
2. Develop or sales of vertical or indoor ag equipment and infrastructure (not control systems or automation, which are included under ELECTRONIC DEVICES SENSORS SYSTEMS category)
3. Note: not distribution, import, or sales of farm machinery and equipment, these are under “Ag inputs distribution and sales” category

*Ag inputs distribution and sales*

1. “Distribution”, “sales”, “retail”, “wholesale”, “supply”, “provision” (but not “manufacturing”) of a range of ag inputs including
  - a. Seeds, plant starts
  - b. Ag chemicals, pesticides, fertilizers
  - c. Biological amendments, inputs
  - d. Animal feed, feed additives and supplements
  - e. Animal health, veterinary products and supplies
  - f. Young live animals (e.g. chicks, fish fry, etc)
  - g. Farm supplies; Aquaculture supplies
  - h. Machinery and equipment (for farm, ranch, aquaculture, fishing, timber operations)
  - i. Parts and services
  - j. etc

2. small minority include “agricultural services” such as contract harvesting, piecework, agronomic consulting services, monitoring, management
3. does not include provision of or contracting ag labor; human resource services were all under “Business and financial services” category
4. if “animal feed”, often in combination with “Marketing, processing, and distribution” category, if company also manufactures or produces the animal feed, which often involves grain or oilseed milling

*Ag production*

1. actual operation of a farm or other agricultural production operation like a fish farm
2. cultivation
3. production
4. often “provision of agricultural services”
5. often mentions actual commodity produced
6. in combination with “Marketing, processing, and distribution” category if vertically integrated business, such as in livestock, oil palm
7. in combination with “Marketing, processing, and distribution” category if fresh market, such as fruit, vegetable, produce
8. in combination with “Marketing, processing, and distribution” category and with “consumer” category if “community supported agriculture (CSA)”, “farm to table”, “locally produced”, etc.

*Marketing, processing, and distribution*

1. post-harvest marketing, distribution, export/import, brokering
2. transportation, logistics
3. processing, milling
  - a. animal slaughter, meat processing, meat packing
  - b. grain milling; feed manufacturing
  - c. oilseed pressing, processing
  - d. cotton ginning
  - e. saw mills

- f. ethanol plants
- 4. other fermentation, extraction, separation, purification for ingredient manufacturing; animal feed additives (such as amino acids, micronutrients, etc.)
- 5. food manufacturing; food brand or category for broad market (i.e. national or commodity-wide)
- 6. wineries; breweries; distilleries
- 7. farmers markets; “local” food marketing

*Consumer products, services, and retail*

- 1. explicit mention of “consumer”, “home”, “household”
- 2. retail
- 3. a specific final product, often branded
- 4. direct marketing or distribution to final consumer (not to stores, restaurants, food service, etc.)
- 5. consumer connected to production/distribution, e.g. community agriculture, farm-to-table, farm share schemes
- 6. mention of “garden”, gardening supplies, garden equipment, indoor gardening systems, if clearly intended for home (not for horticulture or greenhouse industry)

*Unspecified*

- 1.** unable to determine: Combined industry/technology descriptions are too general or missing altogether