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

Felipe De Figueiredo Silva[1]

Gregory D. Graff[2]

David Zilberman[1]

1. University of California, Berkeley, CA
2. Colorado State University, For Collins, CO

Abstract.
Venture capital (VC) investments in privately held startup companies that are intensively engaged in agricultural research and development (R&D) has increased substantially in recent years, from just tens of millions annually in the early 2000s to reportedly more than 7 billion dollars in 2017. These investments are important for several reasons. First, the magnitudes of these VC investments are no longer negligible relative to levels of estimated private sector investments in agricultural R&D, yet they have not typically been accounted for in estimates of agricultural R&D spending. Second, these investments are supporting R&D being conducted by new entrants in a number of industries that have been highly concentrated and where incumbents may have been taking relatively incremental approaches to R&D strategy. Third, R&D by technology based startups represent an important channel for diffusion of results from public sector agricultural research, in both developed and developing countries. This paper describes recent trends in agricultural technology startup companies and the VC investments made in them. This paper also seeks to answer the question of what might account for the upturn in VC investment in agricultural technology startups in recent years. To do so, we construct a dataset of more than 4,500 startups, located in 125 countries. For a subset of these, we have complete financial information on over 10,000 financial transactions from 1981 to 2018, allowing us to study the startup investment life cycles and exit outcomes over time. Results indicate that previous successful exits from agricultural technology startups – in the forms of Initial Public Offering (IPO) and Merger & Acquisition (M&A) – lead to higher investments today. Payoffs from prior investments seem to signal the viability of investments in the agricultural sector. But among exit events, prior IPOs appear to have a stronger effect on new investments than prior M&As. Policy implications of VC investments in agricultural technology startups are discussed.

Key Words. Venture Capital, Agriculture, Innovation, Investments.

Introduction

Innovation in the agricultural and food system has been fundamental in enabling global agriculture to feed the world's growing population. Developments in mechanical, chemical, and biological technologies have contributed to productivity gains that have more than doubled outputs over the last 50 years while hardly changing the aggregate quantity of inputs to agricultural production (Alston et al., 2010). Innovations in harvesting, processing, 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).

Some innovation occurs in the course of ongoing production, processing, and marketing activities: "learning by doing" by farmers and others improve upon existing routines and practices. But, increasingly, innovation occurs as a result of formal research and development (R&D) activities. However, agricultural R&D has generally been highly managed, first by governments supporting agricultural research stations and research at agricultural colleges and universities in order to increase farmer productivity, increase food supply and reduce food prices for consumers. National government efforts were, by the mid-20th century, augmented by an international agricultural research system supported by multiple governments and international organizations. Corporate agribusiness and food firms have also increasingly conducted 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 have increased steadily (Fuglie et al, 2012; Pardey et al, 2016). Globally, annual industry 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. The most recent available global estimate of private sector agricultural R&D was $15.6 billion in 2014 (Fuglie, 2016).

In recent years, there has been a notable emergence of startup companies seeking to develop or apply new technologies in agriculture. These companies are privately-held, and they appear to be receiving significant amounts of equity-based private investment from venture capitalfunds and related sources such as seed, angel, and private equity. According to industry reports, in recent years up to several billion dollars annually have been invested into such agricultural technology (agtech) startup companies in (AgFunder, 2014, 2019; CBInsights, 2017; Finistere, 2019; KPMG, 2018). While the general phenomenon of startup companies introducing new technologies to agriculture is not new, recent rates are unprecedented, both in terms of the number of new starts and the amounts being invested in them. We present evidence that disclosed investments were negligible, typically less than $200 million globally per year, up through 2006, but recently have exploded, exceeding $3 billion annually several times since 2012. Industry sources claim that venture investments in agricultural technology were as high as $6.9 billion in 2018 (AgFunder, 2019).

Accounts vary in term of how prevalent such firm starts and venture investments are across industry sectors and countries. Global accounts have found that historically, private investments in agricultural R&D have been quite low in developing countries. More recent industry reports indicate that robust startup activity can be found even in middle- and lower-income countries, especially the larger economies like Brazil, India, and China. It is also not clear why this surge in venture investment has occurred now in the agriculture industry. What factors account for the recent and dramatic upturn? Finally, it is unclear how much money is, in fact, being invested in such firms and, by extension, available to be expended on their R&D activities. Privately held firms are not subject to the financial reporting requirements that come with public listing. Thus, R&D spending by such farms has remained largely unaccounted for.

The entry and financing of a large number of agricultural technology startups can be expected to impact existing agricultural technology 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 to pursue a larger and more diverse range of R&D projects. Some of the R&D by startups may be complementary to R&D by established organizations. Some startups are even 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 that could improve the research productivity of all agricultural R&D organizations. Still, other startups may be directly competing with established public sector or corporate R&D.

The VC-backed startup is, in essence, a mechanism to contain the financial risks of prospecting and to reduce the technical and market uncertainties of an innovation. While many startups fail in the process, some do prevail in bringing innovation to the market. This 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 leads to exploitative monopolies, but with innovation, new competition erodes monopoly power.

Venture capital investors expect a net return on their investments, thus it stands to reason that conditions in agricultural markets must have shifted in recent years in ways that revised (or awoke) venture investor expectations. This paper addresses the question of what has characterized the increase in the number of new startups and the investments in them. What is behind the recent growth in private investments in agricultural technology startups? It is not yet clear the extent to which this is merely a transient phenomenon, potentially an investment "bubble", or if it constitutes a more enduring shift in the composition and dynamics of agricultural R&D. We explore several explanations for the observed upturn and empirically test several factors that may be correlated with measures of the increase in investment in agricultural technology startups. Indeed, other industries, such as software, internet services, and pharmaceuticals, have endured downturns in venture investment, most famously with the bursting of the Internet tech bubble circa 1999-2000. Yet they continue to exhibit an innovation ecosystem that is routinely refreshed by new startups funded by venture capital in an ongoing cycle. A major question is whether the R&D and innovation system of agriculture may be shifting to look more like these other high-tech industries in the long run.

To investigate these questions, we compile a global dataset of over 4,500 startups in agriculture with more than 10,000 financial transactions, including investments and their exits, combined from three proprietary data sources: Crunchbase, PitchBook (Morningstar), and VentureSource (DowJones). The largest share of the startups (42%) are in the United States, followed by the European Union (21%), with the remainder (37%) located elsewhere in the world, of which significant numbers are in emerging and developing economies. The deal types reported in the financial transactions data include venture capital, seed and angel investments, as well as private equity and debt. Financial transactions also include exits from investments in startups, including initial public offerings (IPOs), mergers and acquisitions (M&As), as well as other types of buyouts of the startup firms. While the data also indicate some bankruptcies and closures of the startup firms, these are clearly incomplete. The firm and transactions data span from 1981 to 2018, allowing us to explore the startup life cycles and exit outcomes over time and across multiple technologies (e.g. agricultural biotech vs farm management software) and subsectors of agriculture (e.g. inputs vs outputs, or crops vs livestock).

Our paper contributes to the literature discussing the determinants of investments into venture capital backed companies and their exit outcomes. See below a discussion of this literature. It complements the well-established literature on private and public R&D expenditure in companies in the agricultural industry and, most important, fills the literature gap in venture capital investments into agriculture. This paper findings suggest that large exit events in the industry have a temporal spillover and increase current investments into startups. We also find that exit outcome is largely explained by the cumulative investment received by the startup during their life-cycle.

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, but 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 and trends of agricultural R&D. The share of global agricultural R&D conducted in middle- and low-income countries is about 45 percent (versus 65 percent conducted in high-income countries), which is a much higher share than overall R&D conducted in low- and middle-income countries, at 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 has actually declined in real terms, growing only very slowly in nominal terms (Pardey et al, 2016). At the same time, public 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 companies are 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 fewe,r 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, very relevant to track R&D spending by small or medium enterprises (SMEs), including venture capital backed companies. While biotechnology startups were observed to have contributed significantly to the rise of genetically 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 not as accessible, 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 quite 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 trigged 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 price and weather uncertainty (Carey and Zilberman, 2002). Farmers only adopt new irrigation technologies when prices exceed a certain threshold.

The same 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 3). 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 2012 might have played a role on the increase on the supply of venture capital investments in agriculture. Yet, Deloof and Vanacker (2018) observe that investments at Belgian startups founded during the 2007 crisis had greater chance of facing bankruptcy.

Several other factors that affect the overall health of the economy can cause changes on the returns to venture capital investment. Groh and Wallmeroth (2016) argue that unemployment affects the venture market via the overall health of the economy. Felix et al. (2013) finds that the unemployment rate has a negative impact on venture capital market. Other disruptions in labor markets that may affect venture capital investments include adjustments in the minimum wage or more generally increases in labor costs. These might incentivize investments in capital-intense technologies that are labor substituting. There is little evidence on the impact of wage rate changes on venture capital investment, but some have investigated the effect of labor rigidity on the demand of venture capital (Jeng and Well 2000; Romain and van Pottelsberghe de la Potterie, 2004). In agriculture, increases on minimum wage for agricultural workers may have an impact on agricultural production and prices, and potentially on the returns to investments in startups in the industry. In California, for example, minimum wage has changed a few times in recent years, with current proposals to increase to US$ 15/hour.

Gompers and Lerner (2004) point out the greater number of rounds and larger amounts of investments and 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).

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 two main approaches used to analyze exit are hazard models and categorical (or binary) choice models. The literature identifies key components that affect both new company starts and existing companies' survival, such as real interest rates (and other macroeconomic variables), company sizes, and industry-specific variables (Homes et al., 2010; Giovannett et al., 2011). Studies that have used categorical models also highlight the role of similar variables in determining the exit outcome (Audretsch, 1994; 1995). Audretsch (1994) finds startup size influences chance of exiting while industry growth rates do not seem to be related to exit timing.

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.

Successful performance early in the startup life-cycle clearly helps to attract more investments, which can lead to a sequence of investments that boost the likelihood of exiting with an IPO. The number of investment rounds is correlated to their ability to attract investments and the quality of the technology develop, therefore to the likelihood of facing sizeable exit deals. Gompers and Lerner (2004) find that firms that exit with an IPO have received larger investments and a greater number of rounds of investments during the life-cycle.

Groh and Wallmeroth (2016) and Jeng and Wells (2000) analyze the determinant of venture capital investments in 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. 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, it is 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 sample for this analysis was built by combining information from three different sources of data on equity investments: Crunchbase, PitchBook, and VentureSource. From each of these sources two types of data were 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 those companies. PitchBook provided data on 2,005 companies and 3,667 deals in their “AgTech vertical” category. VentureSource provided data on 851 companies and 1,779 additional deals in their “Agriculture and Forestry” industry category. Crunchbase provided data on 2,352 companies, with information on just 220 additional deals in their “Agriculture” industry category. These numbers reflect the totals in these data sources minus those firms founded before 1977 and those firms for which investments reported were only private equity or debt without any form of venture capital. The exercise of drawing from multiple data sources was undertaken with an expectation that high rates of overlap across sources would allow for verification of firms and deals, but as Figure 1 shows, we found most companies are present in only one of the three data sources. Just 90 of the most prominent companies are listed in all three sources. This finding in itself suggests that industry reports based upon just one proprietary data source (AgFunder, 2015, 2019; CBInsights; Finistere; KPMG; etc) must be taken as just a partial picture of overall sector trends or performance.

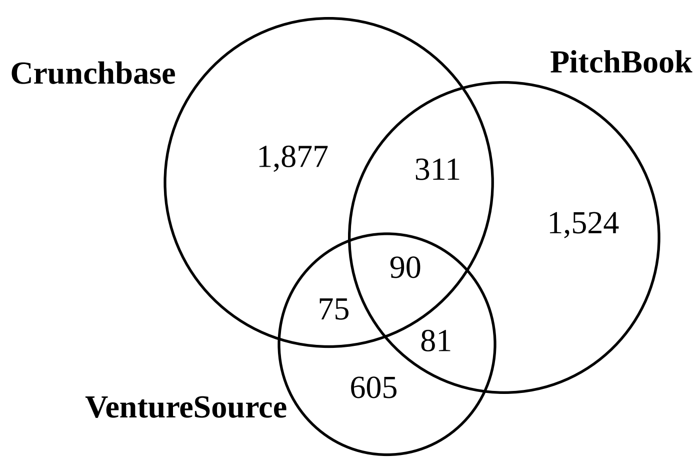

Figure 1. Numbers of startup companies in agriculture, by information source: Crunchbase, PitchBook, and VentureSource.

The company data provide information such as physical and virtual address, current number of employees, company description, technology/activity description, and other overview variables. However, not all companies provide information for all data fields, and moreover each data source has its own approach to the different pieces of information—including even how they report the company's name and address, let alone how they categorize companies and their activities—which made it difficult to merge the three sources. The deals dataset from each source contains information such as the target company's name, type of investment, date of investment, and, for a subset of deals, the amount. Yet, again, variation in reporting across the three data sources, in terms of currency, etc, presented challenges for merging the three.

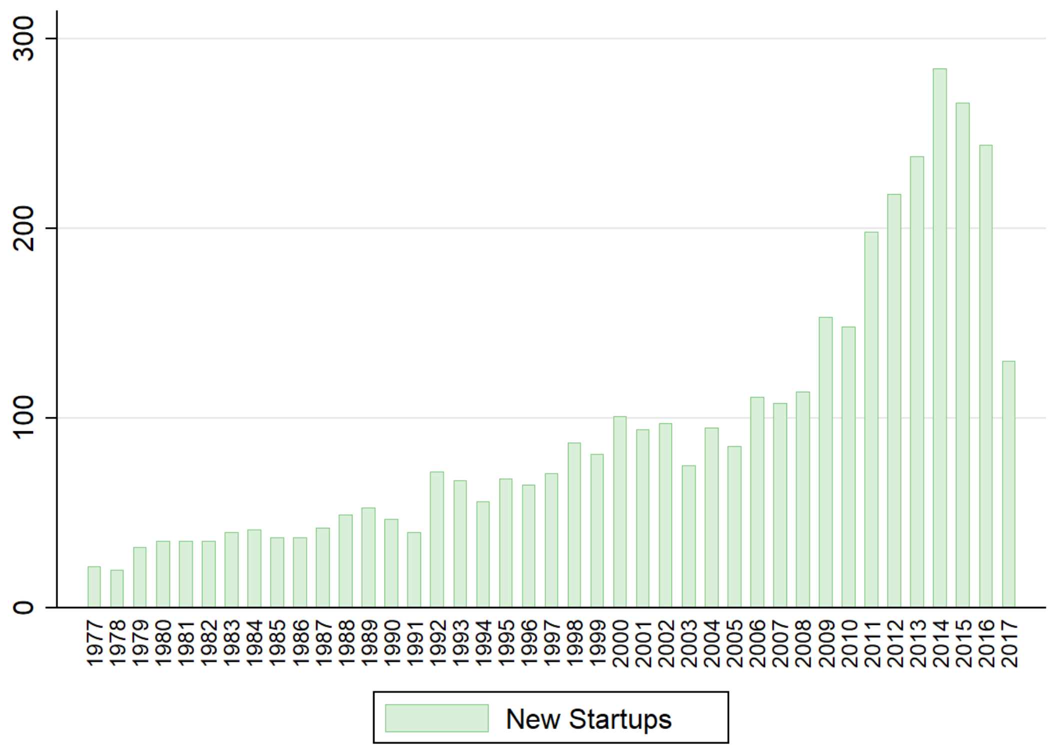

Figure 2. New venture funded startups in agriculture, 1977-2018

Full sample summary statistics

Our overall sample contains 4,552 companies and 13,910 observations of deals (investments or "money-in" deals and exits or "money-out" deals plus closures). In matching companies to deals, however, we find only 1,584 companies with at least 1 deal and 2,968 without any deal information. Of these with deal information we find only 1,092 companies report information on exit. We were able to identify physical address and founding years for most of the companies in the overall dataset. For those without this information but with a date for the first deal we used this information as a proxy for the founding date. In Figure 2 we plot the number of new startups by year. Visually we identify three phases of growth in startups. First from 1977 to 1991, as steady but upward growth with just tens of companies. From 1992 to 2008, growth picked up showing some of the volatility of the overall tech sector with a downturn after the bursting of the bubble in 2000. The number of startups a sharp increase after 2008. (The apparent decrease in startups after 2014 is largely a result of truncation in the data: companies are generally only reported in these data sources upon their first formal equity based investment, which can occur up to several years following formal founding of the company.)

The analysis of Figure 2 raises several questions such as *Why the sharp increase in new startups (increase on demand for venture capital investments) after 2008?* There are several possible explanations. Agricultural commodity prices increased strongly in 2007/2008, then after a sharp decrease back to the 2006 level almost doubled by the years following 2010. Crude oil faced a sharp increase as well but then steady decrease after 2008. Signals from successful exits may have also played a role. There were a couple large IPO and M&A exits during that period including Agria Corp in 2007 and Digital Globe in 2009 that generated around US$ 200 million.

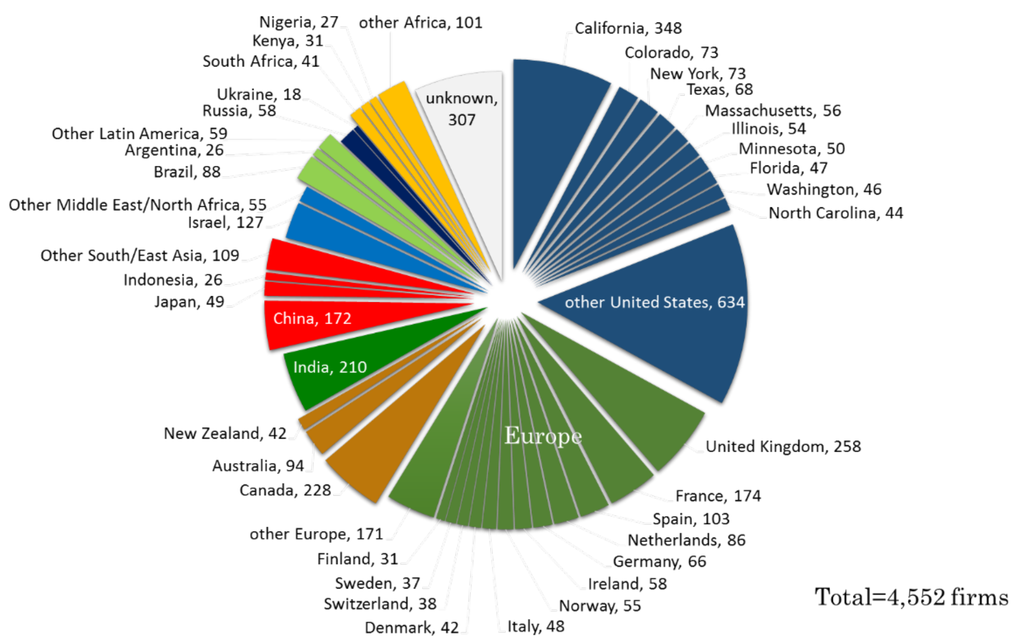

Figure 3. New venture-funded startups in agriculture, 1977-2018, by country of reported address

The richness of this dataset lies on the quality of information across a very diverse set of startups located around the world. Of the overall sample of 4,552 companies, those located in the United States account for approximately 35 percent (or 1,483) of our sample. Out of these, the most report addresses in the state of California, around 4.6% in Colorado, New York, and Texas, and around 3.6% in Massachusetts and Illinois (each). In our sample, 320 (21.6% of the US) startups were in 11 Midwestern states. Around 23% of the startups in the overall sample are in Europe, led by United Kingdom with 261 startups, 173 in France, and 102 in Spain. Canada has 228 startups. Among the emerging markets, India stands out with 210 startups followed by China with 172. South America have 144 startups, led by Brazil with 88 startups. In Africa, South Africa has 41 startups followed by Kenya with 31 startups. This broad geographical distribution of startups plays an important role on the investments received and exit outcome.

Table 1. Number of startups per industry/technology category, 1981-2018

Category	**Number of startups**
Ag Input Technologies and Services	2,482
Software/Data	942
Devices/Sensors	430
Biotech/Genetics/Health	918
Chemicals	230
Equipment or farm machinery	302
Ag Input Distributors / Dealers / Co-ops	678
Ag Producers or Farms	467
Marketing, Processing, Manufacturing	730
Consumer Products or Services	105
Business and Financial Services	539
Online Services and Content	539
Other	1,165

Note: Some companies are categorized in two or more categories.

The three sources of information (Crunchbase, PitchBook, and VentureSource) made available several data fields describing the company, their activities and the technology they are working on. However, their categorization schemes do not match, and company reporting was very heterogeneous within the descriptive fields that were available. We developed a categorization for the startups drawing on these fields and based on industry observations (see Graff et al 2014), as detailed in the Appendix. Table 1 displays the number of startups in each of these categories. Most of these startups are in the umbrella category *Ag Input Technologies and Services*, which includes the categories *Software and Data* (942 startups) *Biotech, Genetic and Health* (918 startups). The two categories obtained more than 60% of the investments in 2016. Some of the technologies been developed by these startups are very interdisciplinary which led us to categorize them in more than one category – 27% of startups in the full dataset (4,552) and 30% of the small sample (1,328 startups) are classified in two or more categories.

Focused subsample with reported investment data

In the overall dataset, many of the companies do not report investment deals, and of those that do, some of do not report amounts of investments. After constructing variables for investments and exits we dropped all companies that did not have at least one money-in investment with reported amount. The number of companies in this subset is just 29% of the overall sample. Subsequent data summaries in this section are drawn from this subsample with reported investments. This selection implies that we are likely underestimating the number of (new) startups, the values of investments in agricultural startups, and the number of exits.

Money-in investments represent all types of investments received to realize startup performance: Grant, Angel-Seed, VC Early Stage, VC Late Stage, Debt, and Private Equity. Figure 3 displays the total money in investments per type and year (with incomplete information for 2018.) Following the sharp increase on new startups, total money in also exhibited a sharp increase in the late 2000's. Our data suggest that venture capital represents most of these investments in recent years.

Even though money-in investments have increased since 2008 the composition of these investments has been fairly stable among three types: VC early stage, VC late stage, and Debt. The composition of investments also varies by countries and regions. Our data suggests that VC early stage represents the majority of the money in in agricultural startups in countries in the

European Union. Angel and seed investments represent a larger share of total investments in the United States. Also, in the United States, funding from the most traditional financing instrument, banks, is more common – the share of Debt to total money in is much larger in the United States.

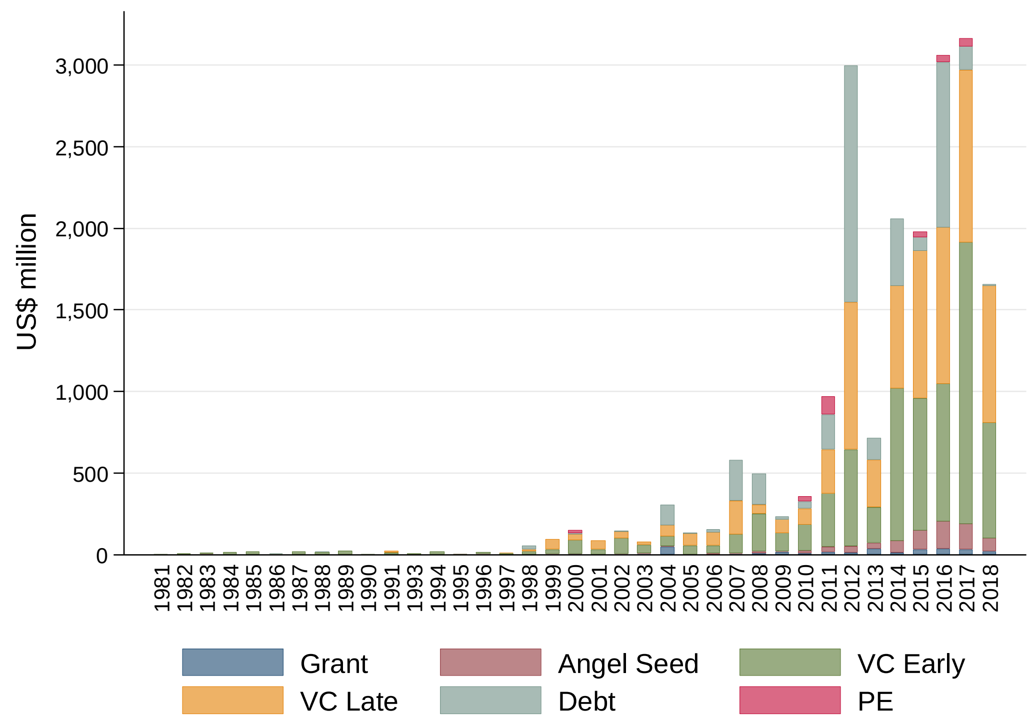

Figure 3. Money-in investments into agricultural startups

In Table 2 we display the total money in investments for each of the technology categories in Table 1. To build this table, for the startups in more than one category we divided the total investment by the number of categories and include the outcome in each of the categories.

Table 2. Money-in investments per category and year, 1990-2018 (earlier years dropped due to preponderance of zero values)

	Online service	Business finance service	Biotech genetic health	Chems. materials	Elect. Devices	Software	Machine Equip.	Ag.input distrib.	Ag prod	Market. Process. Distrib.	Cons. prod. retail	Unsp.
1990	0.00	0.00	2.80	0.00	0.00	0.00	0.00	0.50	0.00	2.50	0.00	0.00
1991	0.00	0.00	15.15	0.00	6.05	0.00	0.00	0.00	3.00	1.20	0.00	0.00
1992	0.00	0.00	5.60	0.00	0.00	0.00	0.00	0.00	2.00	2.25	0.00	0.00
1993	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.60	0.00	0.00
1994	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	20.00	0.00	0.00
1995	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.00	0.30	0.30	2.00	0.00
1996	0.00	1.19	1.19	1.19	0.00	0.00	0.00	2.89	0.00	10.00	0.00	0.00
1997	0.00	0.00	7.79	0.00	1.06	1.06	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	2.03	19.03	2.73	0.00	2.32	0.00	2.56	2.50	26.16	0.00	0.00
1999	10.57	7.25	68.13	2.36	0.00	2.39	0.00	10.02	0.00	1.50	0.00	0.00
2000	68.00	58.38	53.09	7.88	0.28	6.50	0.00	13.38	0.00	1.21	0.00	0.00
2001	1.00	1.00	48.44	8.00	1.18	3.23	8.00	15.45	0.00	0.49	0.00	0.00
2002	0.00	0.00	14.77	41.54	2.43	0.00	0.00	0.00	0.00	5.10	0.00	80.00
2003	0.00	5.00	26.43	17.50	0.27	0.27	11.00	5.00	1.31	17.44	0.00	0.00
2004	0.00	0.00	59.00	18.48	0.00	186.88	12.51	19.52	0.00	7.80	0.00	0.00
2005	0.04	5.28	30.46	26.46	1.35	0.54	69.01	4.78	0.00	2.00	0.00	0.00
2006	2.25	0.00	53.42	1.52	2.00	13.72	33.12	6.14	4.00	38.83	0.00	0.00
2007	0.25	30.95	324.69	21.08	2.92	56.14	4.83	153.40	7.62	7.40	0.00	0.00
2008	4.00	19.75	111.25	36.40	0.80	66.77	59.66	6.09	58.13	151.86	0.00	0.00
2009	4.33	20.70	59.77	16.54	3.43	29.58	16.61	5.20	56.82	33.72	0.00	0.00
2010	4.22	5.02	156.93	9.00	10.08	17.96	5.13	43.12	19.90	75.08	14.34	0.00
2011	4.36	19.40	189.96	36.65	24.97	114.06	37.20	250.07	52.97	239.32	16.89	0.00
2012	18.76	14.71	359.84	66.61	18.70	1388.65	2.78	285.97	409.36	424.57	0.88	0.00
2013	9.72	4.90	357.48	78.51	30.94	24.84	32.08	36.65	16.12	95.87	1.93	0.00
2014	47.15	58.64	645.56	112.15	65.69	183.85	58.19	403.56	168.76	356.06	6.69	4.09
2015	145.31	111.73	635.13	9.96	56.52	198.94	208.81	104.00	137.89	139.71	2.25	7.93
2016	315.91	253.00	1724.74	44.76	158.26	236.98	59.96	142.47	62.81	201.14	4.73	12.74
2017	348.83	85.03	1200.83	60.69	222.16	546.47	77.75	260.94	37.83	178.75	15.06	8.42
2018	555.40	163.44	220.15	9.41	113.35	191.17	58.76	231.21	65.20	124.25	0.00	57.35

The shift of investing into the agriculture industry may have been driven by large positive swings in the commodities prices during downturn in the overall economy around the 2007 crisis. To test this hypothesis, we utilize commodity prices changes over time. In Figure 4 we display a standard aggregated agricultural price index, obtained from FAO. (Given that the series ends in 2017, we use the average growth rate of the last 5 years to forecast 2018 values).

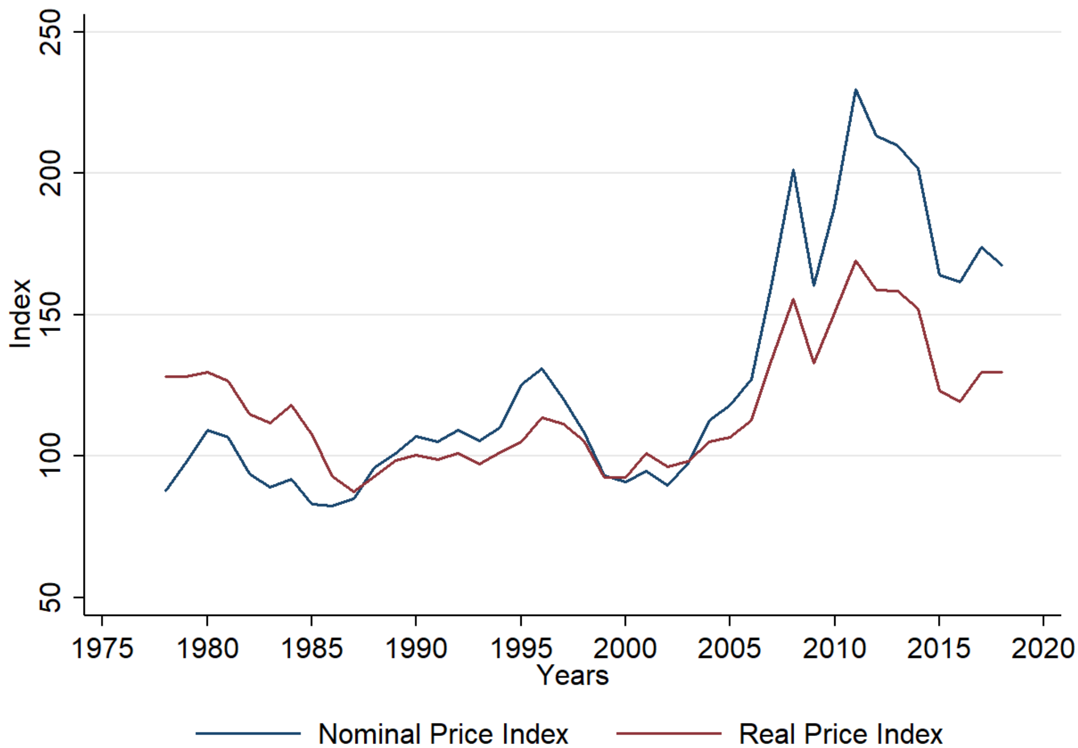

Figure 4. FAO agricultural price index (Nominal and Real)

In our sample, not all the startups have provided information on their exit. We expect that companies that have faced bankruptcy or even closed do not report as those that have successfully exit with an IPO or M&A. Among those companies that have reported, we observe a steady amount of companies exiting. In this case, we followed a two-step procedure to identify startups that might have underreport and assign them an exit date. First, we calculated the time between the last investment in and the exit outcome of startups that closed; on average, 35 months. Second, rather than using this average, we used the 95th percentile to minimize the chances of false positive (assigning closed when they are not). All startups with more than 78 months from the last investment in were assigned an exit date associated to the last investment in plus the 78 months. Following this procedure, we identified 197 startups with possible closing not reported. Then, in our sample, we assume they have exited the market in 2018. Gompers and Lerner (2004) used a similar threshold to define possibly closed companies. However, there is a caveat in this procedure, almost two-thirds of the startups in our sample did not report a deal (1,584 reported at least one deal). We then used the founding date or year as the initial date. Those startups that did not report a founding year nor had any investment were dropped.

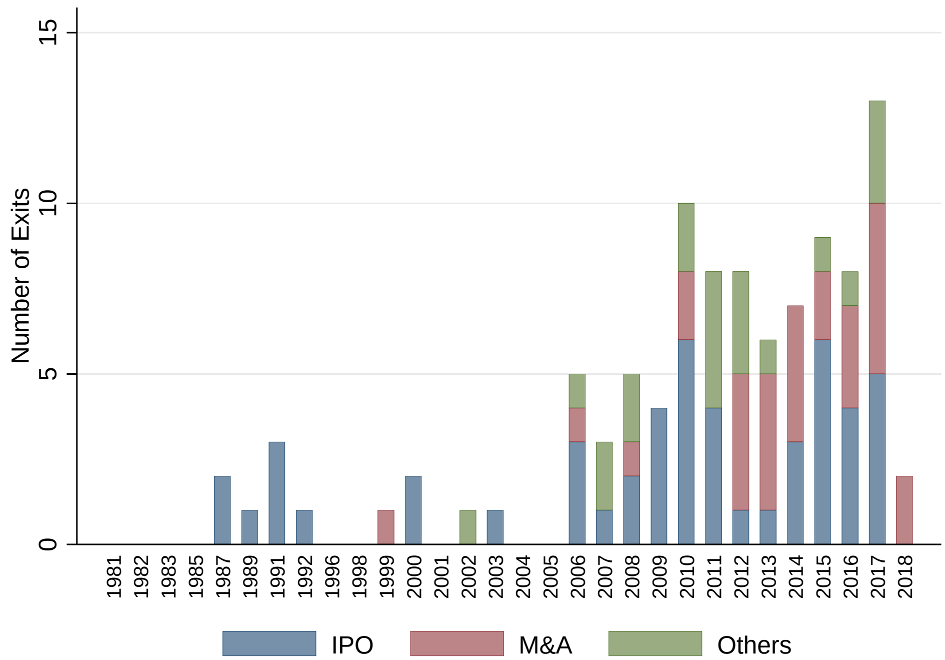

Figure 5. Exit events over the period 1981-2018

The return to investment is represented in the exit event. The most desired outcomes are Initial Public Offering (IPO) and Merger & Acquisition (M&A), in this order. These two outcomes generate the most return to the investor while other outcomes might payback the investment via sale of the startup’s assets. In Figure 5 we display the number of exits per type for startups that have reported exit information. We do not graph the number of *closed* startups given that this information might be misreported. Interestingly, the number of exits, specially IPO and M&A increased a few years before the sharp increase in the number or new startups and investments in. This pattern corroborates the idea that large IPOs and M&As attract investments into the industry. In Figure 6, we display the amount raised in both types of exit.

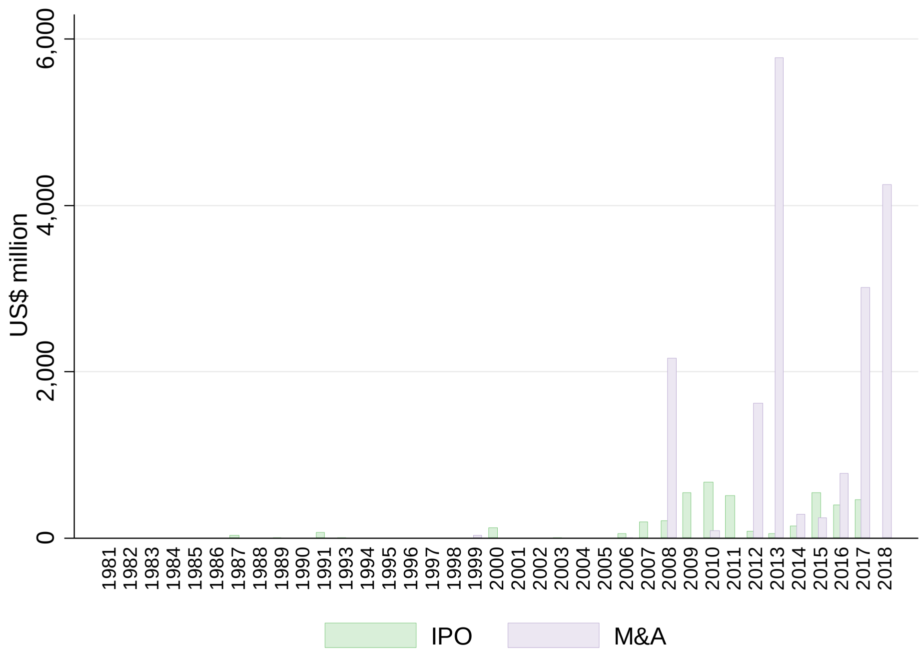

Figure 6. Money out at IPO and M&A events in nominal US$ 1981-2018

As a result of these changes to the dataset, for the econometric model estimations, we keep in our sample only the startups that have reported at least one money-in investment, which generates a sample of 1,348 startups with 2,836 observations. Even though we drop two-third of the observations we trust that our remaining sample represents closest to the true population of venture capital backed companies in agriculture analyzed in the literature. For sake of comparison, of those that reported a country information. in this sample, 41% of the startups are in the United states while 23% are in the European Union. These are somewhat higher values that observed in the overall dataset (Figure 2) indicating that full financial information is more commonly available for the US and European firms listed in the primary data sources. Utilizing a smaller sample of companies implies that, in our analyses, we would be overestimating the true effect of large exit events, industry-specific characteristic and total money in given that our sample is probably composed of the more successful companies, those that received the largest investments and experienced the largest exits.

Empirical Strategy

In this section, we describe our empirical strategy to test some of the hypotheses laid over in the previous section. Specifically, we test two hypotheses. First, we investigate the relation between agricultural prices and investments in startups in this industry. To test this hypothesis, we investigate the effect on investments of three prices - aggregated commodities prices (P_{gt}), from both FAO and World Bank, and soybean prices for the United States. As argued before, large positive price swing might have shift venture capital toward startups in agriculture. These effects might not be felt contemporaneously but with some k lagged years. In Equation (1) we test both cases. Both the number of startups (Figure 2) and the dollar amount invested in startups (Figure 3) have drastically increased after 2010. Therefore, we also test whether the price effect might have change after 2010. To do so, we add an interaction between price and a dummy equal 1 after 2010. We expect prices to have a positive impact on investments in and, even larger, after 2010.

Second, we examine whether large exit events have a herd effect and boost investment in these startups. Gompers and Lerner (2004), Jeng and Well (2000) and the thereafter literature found evidence that exit events (ee_t) disrupt the investment market. In the literature, most studies of the times focus in IPOs (Gompers and Lerner, 2004; Jeng and Well, 2000). For instance, Jeng and Well (2000) tested both the contemporaneous and lagged effect of IPOs on venture capital investments. Rather than only focus on IPOs, we also look at the M&A exits type. We expect a positive effect of exit events in investments in.

In Equation (1), our unit of observation is the realized investments within a year t obtained by the startup i. Some startups were able to obtain more than one investment per year. Our final sample incorporates investments from 1981 to 2018 and add up to 2414 observations.

$$y_{jit} = \alpha + \beta_1 P_{gt-k} + \delta_1 ee_{t-k}^{m\&a} + \delta_2 ee_{t-k}^{ipo} + X_i\theta + X_j\mu + u_{jit} \tag{1}$$

where X_i and X_j are startups and investment control variables, u_{jit} is the random error term clustered at the startup level. $\beta_1$represents the prices effect on investments in, and δ_1 and δ_2 represents effects of exit events on the startup's current investment. Our sample is very heterogenous. These startups are at different stages in their lifecycle, different locations (state within the US and other countries), in geographical clusters, and in different sub-niches. To obtain an unbiased test of these hypotheses, we control for these factors. We also add a few country and/or continent dummy (e.g. Europe) variables to capture these differences. In addition, we also account for size and included a categorical variable for number employees (0 to 5 – very small to very large). We add a variable *age* to capture their stage in the startup lifecycle.

Investments per industry sector

To investigate whether Money In and Exit Events affect investments at industry category level we estimate Equations (2). We regress total investment in per category and year on prices and exit events to the test the hypotheses mentioned above. We build a balanced panel of 11 *c* sector categories described in the Appendix per year (from 1981-2018) and estimate a fixed effects model.

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

where X_c represents the categories fixed effects and u_{ct} is a random error term. Some of these startups are categorized in more than one category due to the interdisciplinary of the technologies been developed. We then split these investments by the number of categories (e.g. if startup A appears in two categories, we multiply the investments by 0.5 and include them in both).

Results

The effect of venture capital investments has several facets in the agricultural industry. These investments represent at least 20% of the total private investments in R&D in the industry. They directly affect innovations production and disrupt the old way of producing new technology, mainly by public institutions and large companies. Dixit and Pindyk (1993) analysis of investments under uncertainty is used in this paper to identify the factors and events that generated the large hurdle rate to shift these investments into agriculture. In this section, we present the results for Equation (1) and Equation (2), which explain the current level of investments. Table 3, 4, and 5 presents the regression results for the models related to the effect of exit events and agricultural prices in investments in startups.

Table 3. The effect of exit events and price on investments in at startup level (fixed Effects) – Equation 1.

Variable	S.1	S.2	S.3	S.4	S.5	S.6
IPO	0.0005	0.0014	0.0004			
	(0.0036)	(0.0036)	(0.0036)			
Lagged IPO (2 yr)				0.0095**	0.0095**	0.0093**
				(0.0050)	(0.0040)	(0.0045)
M&A	0.0002	0.0003	0.0003			
	(0.0005)	(0.0004)	(0.0004)			
Lagged M&A (2 yr)				0.0006**	0.0006**	0.0005**
				(0.0003)	(0.0003)	(0.0003)
Price FAO	0.0448*			0.0116		
	(0.0249)			(0.0207)		
Price Soy		0.0151*			0.0045	
		(0.0087)			(0.0096)	
Price WB			0.0920*			0.0301
			(0.0491)			(0.0450)
Crisis				2.936	2.932	2.927
				(3.756	(3.796	(3.731)
Constant	-6.226	-5.107	-6.852	-3.908	-3.742	-4.489
	(7.298)	(7.050)	(7.400)	(5.174)	(6.032)	(5.933)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Location Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.10	0.10	0.10	0.10	0.10	0.10
N	2417	2417	2417	2414	2414	2414

Note: Standard errors in parenthesis. *** for 1% significance, ** for 5% and * for 10%. IPO and M&A are in US$ million; Price FAO and Price WB are price indexes based on 2004-2006 average and 2010 respectively; Price Soy is nominal prices in US$/metric tons. Dependent variable ($ deals size) is in US$ million.

In Table 3 we present the considering contemporaneous and lagged effects of exit events in investments in while prices are only considered contemporaneously. These results corroborate our analysis of the data done so far that prices are positively associated to investments in startups. An increase of 10 point in the agricultural price index (FAO) generates an increase of around US$ 400 thousand while an increase of US$ 100 (equivalent to 7.6% of the price in 2011) the soybean prices would generate an increase in investments in of US$ 1.5 million. However, price effects go away as we add the lagged variables of exit events. Results are robust across the estimations.

Our results suggest that both previous IPO and M&A (lagged 2 years) lead to higher investments today. IPOs have a much stronger effect. An increase on the IPO deals of US$ 1 million leads, on average, to an increase of at least almost US$ 9,000 on current level of investment. M&A generates an increase of at least, on average, US$ 1,000 on current level of investments. Both exit outcomes can be interpreted as a large hurdle and might have shift investments into the agriculture industry. These results are in line with the literature (Gompers and Lerner, 2006; Jeng and Wells, 2000).

These three variables are statistically significant when we lagged all the three of them in addition to control for year fixed effects (see Table 4). Results are also larger than those reported in Table 3 probably due to the lagged prices and year fixed effects. Results from Table 3 and 4 corroborates the heard effect in the venture capital market where large exit events such as the most recent IPO of Beyond Meat which raised more than US$ 1.4 billion in May of 2019.

However, we haven't examined whether large positive swing in agricultural prices might have shift investments towards startups in agriculture. In Table 5 we display a regression in which we add an interaction between price and a dummy equal to 1 for 2010 up. We selected 2010 based on Figure X, which investments in increased along the drastic increase in agricultural prices. There is a clear change in sign after 2010. These results indicate that investments increase after the sharper increase in prices in 2010 and suggest that prices might have generated a shift of venture capital investments into startups into agriculture. However, there are two limitations in these results, we find a negative price effect prior to 2010 and it is missing to add an alternative investment price. As we argued in the previous section, the ratio of these two prices will better capture the price effect. In future research we will incorporate this analysis.

Table 4. The effect of exit events and price on investments in at startup level (fixed Effects) – Equation 1, lagged variables.

Variable	S.7	S.8	S.9
Lagged IPO (2 yr)	0.0115***	0.0135***	0.0104**
	(0.0045)	(0.0048)	(0.0043)
Lagged M&A (2 yr)	0.0107**	0.0093*	0.0101*
	(0.0052)	(0.0054)	(0.0053)
Price FAO (2 yr)	0.1162***		
	(0.0405)		
Price Soy (2 yr)		0.0569***	
		(0.0198)	
Price WB (2 yr)			0.2841***
			(0.0989)
Constant	-26.83***	-30.84***	-31.97***
	(8.10)	(9.43)	(9.80)
Industry Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Location Dummy	Yes	Yes	Yes
Age	Yes	Yes	Yes
R2	0.12	0.12	0.12
N	2414	2414	2414

Note: Standard errors in parenthesis. *** for 1% significance, ** for 5% and * for 10%. IPO and M&A are in US$ million; Price FAO and Price WB are price indexes based on 2004-2006 average and 2010 respectively; Price Soy is nominal prices in US$/metric tons. Dependent variable ($ deals size) is in US$ million.

Looking at the control variables, we have argued that location plays an important role for both supply and demand of venture capital investments. In this first look, we add to the model two location dummies, United States and European Union. The US dummy is consistently positive and significant throughout these models while the EU dummy is negative and only occasionally significant. This corroborates common observations that startups in the US receive larger investments compared to non-US startups. Another expected result is the positive effect of age on investments. Companies that have been in the market longer receive more investment. Throughout we also find that larger startups, in terms of number of employees, receive larger investments, as expected. These expected results suggest that these estimations are correctly capturing the determinants of investments in startups.

Table 5. The effect of exit events and price on investments in at startup level (fixed Effects) – Equation 1 with break in prices

Variable	S.10	S.11	S.12	S.13	S.14	S.15
IPO	-0.0031	-0.0027	-0.0031			
	(0.0039)	(0.0034)	(0.0039)			
Lagged IPO (1 yr)				0.011***	0.011***	0.011***
				(0.0036)	(0.0034)	(0.0036)
M&A	0.0000	0.0000	0.0000			
	(0.0003)	(0.0003)	(0.0003)			
Lagged M&A (1 yr)				0.0006	0.0006	0.0006
				(0.0005)	(0.0004)	(0.0004)
Price FAO	-0.104***			-0.096**		
	(0.0392)			(0.0480)		
Price FAO * Dummy [2010+=1]	0.121***			0.091***		
	(0.0297)			(0.0271)		
Price Soy		-0.043**			-0.0333	
		(0.0171)			(0.0203)	
Price Soy * Dummy [2010+=1]		0.049***			0.035***	
		(0.0115)			(0.0111)	
Price WB			-0.175**			-0.1800*
			(0.0788)			(0.0974)
Price WB * Dummy [2010+=1]			0.215***			0.166***
			(0.0514)			(0.0492)
Constant	0.13	0.41	-0.54	-2.22	-3.41	-1.84
	(5.01)	(5.57)	(5.72)	(6.35)	(6.60)	(6.95)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Location Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.10	0.10	0.10	0. 10	0. 10	0.10
N	2417	2417	2417	2416	2416	2416

Note: Standard errors in parenthesis. *** for 1% significance, ** for 5% and * for 10%. IPO and M&A are in US$ million; Price FAO and Price WB are price indexes based on 2004-2006 average and 2010 respectively; Price Soy is nominal prices in US$/metric tons. Dependent variable ($ deals size) is in US$ million.

Industry category analysis

These already observed effects might differ systematically across different technology or industry categories. We estimate several models to test for this. Table 6 and 7 present some of the results. Results in Table 6 are similar to those found previously. Both IPOs and M&As contemporaneously increase investment within a given category. Results regarding the price effects are much more robust than in the previous models. While prices after 2010 have a significant positive effect on investments, prices prior 2010 have no effect on investments.

Table 6. The effect of exit events and price on investments in at industry category level (fixed Effects) – Equation 2.

Variable	IC.1	IC.2	IC.3	IC.4	IC.5	IC.6
IPO	0.085*	0.103**	0.084*	0.060	0.072	0.054
	(0.045)	(0.041)	(0.045)	(0.047)	(0.044)	(0.048)
M&A	0.014**	0.015**	0.016**	0.012**	0.012**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Price FAO	0.715***			0.375		
	(0.240)			(0.308)		
Price FAO * Dummy [2010+=1]				0.262*		
				(0.149)		
Price Soy		0.254***			0.118	
		(0.088)			(0.114)	
Price Soy * Dummy [2010+=1]					0.113*	
					(0.060)	
Price WB			1.443***			0.805
			(0.488)			(0.594)
Price WB * Dummy [2010+=1]						0.503*
						(0.269)
Constant	-104***	-958***	-112***	-76.8**	-68.4**	-84.3**
	(33.27)	(31.50)	(35.63)	(36.661)	(34.466)	(38.627)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.23	0.23	0.23	0.24	0.24	0.24
N	456	456	456	456	456	456

Note: Standard errors in parenthesis. *** for 1% significance, ** for 5% and * for 10%. IPO and M&A are in US$ million; Price FAO and Price WB are price indexes based on 2004-2006 average and 2010 respectively; Price Soy is nominal prices in US$/metric tons.

Table 7. The effect of exit events and price on investments in at industry category level (fixed Effects) – Equation 2 with *lagged variables*

Variable	IC.7	IC.8	IC.9	IC.10	IC.11	IC.12
Lagged IPO (1 yr)	0.189***	0.188***	0.219***	0.188***	0.188***	0.219***
	(0.044)	(0.045)	(0.041)	(0.044)	(0.045)	(0.041)
Lagged M&A (1 yr)	0.011*	0.012*	0.014**	0.011	0.012*	0.014**
	(0.007)	(0.007)	(0.007	(0.007)	(0.007)	(0.007)
Lagged Price FAO (1 yr)	0.554**			0.564**		
	(0.238)			(0.243)		
Lagged Price Soy (1 yr)		1.108**			1.114**	
		(0.482)			(0.488)	
Lagged Price WB (1 yr)			0.144*			0.144
			(0.088)			(0.089)
Crisis				-5.730	-2.280	3.277
				(27.257)	(27.014)	(26.887)
Constant	-92.0***	-98.0***	-71.3***	-92.8***	-98.3***	-71.2***
	(33.06)	(35.35)	(31.60)	(33.29)	(35.50)	(31.64)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.27	0.27	0.27	0.27	0.27	0.27
N	444	444	444	444	444	444

In Table 7 we present results for two different set of variables, with and without a dummy variable for the 2007/08 crisis. For sake of comparison, an increase of US$100 in the soy price would lead to an increase of US$ 110 million in investments in. Note that the dependent variable in these models are the sum of investments in one of the 11 categories (see Table 2 for values on this variable). This variable is much larger compared to investments in startups. In Table A1 (in Appendix) we display additional results in this estimation controlling for the 2007/08 financial crisis. All regressions displayed in that table indicate a decrease in investments during the crisis. These results also corroborate the hypotheses that exit events and higher prices are associated with larger money-in investments.

At this level of aggregation, we cannot use the same control variables as previously in the models with startups as the cross-section unit, including age, number of employees, and country. Even though fixed effects for industry categories are jointly statistically significant, some individual categories are not. For example, a few of these variables have larger values compared to the category 'Unspecified' (see Appendix to understand how we categorize these firms). They are (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. In Table 2, the level of participation of these four categories in total investments in this industry is noticeable.

Conclusions

These analyses so far shed light in an important source of research and development investment in agriculture. It contributes to the literature by filling out the lack of studies focusing in in venture capital backed companies in agriculture. With that said, in future research we will focus in the determinants of the exit likelihood and improve the current models incorporating alternative investment prices, macro-economic variables and a measure of industry investment.
[tbd]

References

AgFunder, *AgTech Investing Report – 2014*, San Francisco, 2015.

AgFunder, *AgriFood Tech Investing Report – 2018*, San Francisco, 2019.

Alston, Julian M., Matthew A. Andersen, Jennifer S. James, and Philip G. Pardey, *Persistence Pays: U.S. Agricultural Productivity Growth and the Benefits from Public R&D Spending*, New York: Springer, 2010.

Audretsch, David B. "Business survival and the decision to exit." Journal of the Economics of Business 1, no. 1 (1994): 125-137.

Audretsch, David B. "The propensity to exit and innovation." Review of Industrial Organization 10, no. 5 (1995): 589-605.

Carey, Janis M., and David Zilberman. "A model of investment under uncertainty: modern irrigation technology and emerging markets in water." American Journal of Agricultural Economics 84, no. 1 (2002): 171-183.

CBInsights, Ag Tech Heats Up: 5 Trends Shaping the Future of Farming & Agribusiness, December 12, 2017. Available at https://www.cbinsights.com/research/agtech-trends-shaping-the-future-of-farming-expert-intelligence/

Deloof, Marc, and Tom Vanacker. "The recent financial crisis, startup financing and survival." Journal of Business Finance & Accounting 45, no. 7-8 (2018): 928-951.

Dixit, Avinash K., and Robert S. Pindyck. *Investment under Uncertainty*. Princeton University Press, 1994.

FAO, *The State of Food Security and Nutrition in the World 2018, Building climate resilience for food security and nutrition*. Food and Agricultural Organization, Rome, 2018.

Félix, Elisabete Gomes Santana, Cesaltina Pacheco Pires, and Mohamed Azzim Gulamhussen. "The determinants of venture capital in Europe—Evidence across countries." Journal of Financial Services Research 44, no. 3 (2013): 259-279.

Finistere Ventures, *2018 Agtech Investment Review*, San Diego, 2019

Fuglie, Keith O., Paul W. Heisey, John L. King, Carl E. Pray, Kelly Day-Rubenstein, David Schimmelpfennig, Sun Ling Wang, and Rupa Karmarkar-Deshmukh. *Research Investments and Market Structure in the Food Processing, Agricultural Input, and Biofuel Industries Worldwide*. ERR-130. U.S. Dept. of Agriculture, Economics Research Service, December 2011.

Fuglie, Keith, Paul Heisey, John King, Carl E. Pray, and David Schimmelpfennig. "The contribution of private industry to agricultural innovation." *Science* 338, no. 6110 (2012): 1031-1032.

Fuglie, Keith, “The growing role of the private sector in agricultural research and development world-wide,” *Global Food Security* 10 (2016): 29-38.

Giovannetti, Giorgia, Giorgio Ricchiuti, and Margherita Velucchi. "Size, innovation and internationalization: a survival analysis of Italian firms." Applied Economics 43, no. 12 (2011): 1511-1520.

Gompers, Paul Alan, and Joshua Lerner. The Venture Capital Cycle. MIT Press, 2004.

Gordon Rausser, Ben Gordon, and James Davis. "Recent Developments in the California Food and Agricultural Technology Landscape." ARE Update 21(4)(2018):5-8. University of California Giannini Foundation of Agricultural Economics. Available at https://giannini.ucop.edu/publications/are-update/issues/2018/21/4/recent-developments-in-the-california-food-and-agr/

Gordon, Ben; Olena Sambucci; Itai Trilnick; and David Zilberman. “Research, Innovation, Supply Chains, and Precision Agriculture in California” in California Agriculture Dimensions and Issues (2018). Available at https://giannini.ucop.edu/publications/cal-ag-book/

Graff, Gregory, Annabelle Berklund, and Kathay Rennels, *The Emergence of an Innovation Cluster in the Agricultural Value Chain along Colorado’s Front Range*, Colorado State University, November 2014.

Groh, Alexander Peter, and Johannes Wallmeroth. "Determinants of venture capital investments in emerging markets." Emerging Markets Review 29 (2016): 104-132.

Holmes, Phil, A. Hunt, and Ian Stone. "An analysis of new firm survival using a hazard function." Applied Economics 42, no. 2 (2010): 185-195.

Hu, Ruifa, Qin Liang, Carl Pray, Jikun Huang, and Yanhong Jin. "Privatization, public R&D policy, and private R&D investment in China's agriculture." *Journal of Agricultural and Resource Economics* (2011): 416-432.

Huffman, Wallace E. & Robert E. Evenson, *Science for Agriculture: A Long-Term Perspective*, Blackwell Publishing, 2006.

Jeng, Leslie A., and Philippe C. Wells. "The determinants of venture capital funding: evidence across countries." Journal of corporate Finance 6, no. 3 (2000): 241-289.

Kolympiris, Christos, and Nicholas Kalaitzandonakes. "The geographic extent of venture capital externalities on innovation." Venture Capital 15, no. 3 (2013): 199-236.

Kolympiris, Christos, Nicholas Kalaitzandonakes, and Douglas Miller. "Location choice of academic entrepreneurs: Evidence from the US biotechnology industry." Journal of Business Venturing 30, no. 2 (2015): 227-254.

Kolympiris, Christos, Sebastian Hoenen, and Nicholas Kalaitzandonakes. "Geographic distance between venture capitalists and target firms and the value of quality signals." Industrial and Corporate Change 27, no. 1 (2017): 189-220.

KPMG, *Venture capital investment in agtech continues to soar*, 30 October 2018. Available at https://home.kpmg/au/en/home/insights/2018/08/venture-capital-investment-agtech.html.

Pardey, Philip G., and Nienke M. Beintema. *Slow Magic: Agricultural R&D a Century After Mendel*. Agricultural Science and Technology Indicators Initiative (ASTI), International Food Policy Research Institute (IFPRI), Washington,D.C., 2001.

Pardey, Philip G., Nienke M. Beintema, Steven Dehmer, and Steven Wood, *Agricultural Research: A Growing Global Divide?* Agricultural Science and Technology Indicators Initiative (ASTI), International Food Policy Research Institute (IFPRI), Washington,D.C., 2006.

Pardey, Philip G., Julian Alston and Vernon Ruttan, “The Economics of Innovation and Technical Change in Agriculture,” Ch. 22 in *Handbook of Economics of Innovation*, Volume 02, Elsevier, 2010.

Pardey, Philip G., Connie Chan-Kang, Steven P. Dehmer, and Jason M. Beddow. "Agricultural R&D is on the move." *Nature News* 537, no. 7620 (2016): 301.

Pe'er, Aviad, and Thomas Keil. "Are all startups affected similarly by clusters? Agglomeration, competition, firm heterogeneity, and survival." *Journal of Business Venturing* 28, no. 3 (2013): 354-372.

Puri, Manju, and Rebecca Zarutskie. "On the life cycle dynamics of venture-capital-and non-venture-capital-financed firms." *The Journal of Finance* 67, no. 6 (2012): 2247-2293.

Romain, Astrid, and Bruno van Pottelsberghe de la Potterie. "The determinants of venture capital: a panel data analysis of 16 OECD countries." (2004).

Sunding, David, and David Zilberman. "The agricultural innovation process: research and technology adoption in a changing agricultural sector." Handbook of agricultural economics 1 (2001): 207-261.

Appendix. Categorization of startup firms by industry and technology

In our sample, startups self-report their industry code and segment. We queried and read the startups description and activity information fields to assign them to the categories in Table 1, in order to introduce field specific controls in the estimations. The list below describes in more detail the types of business include 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 ONLINE category
8. Publishing, catalogues, information for industry clients, may be in combination with ONLINE category
9. Consulting, advisory services
10. Contract research services

Online services and content

1. “Online,” “website,” “web,” or “portal”; often “platform” but not always
2. “B2B” or “B2C”, but almost always in combination with another appropriate industry 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 biological 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. <u>not if</u> "biopesdicides" or <u>not if</u> explicitly described as protein or peptide, etc., which were included in BIOTECH)
3. Mention of a specific class of chemical compounds that characterize products
4. Inert materials with beneficial properties as soil additives, fillers, growth media, polymers, 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. Lighting or LED systems for contained or indoor agriculture
4. Control systems
5. Robots, drones, unmanned or autonomous vehicles (UAVs)
6. Note: technologies/products that would be in "electrical engineering", not machinery or equipment that would be considered "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: <u>not</u> distribution, import, or sales of farm machinery and equipment, these are under AG INPUTS DISTRIBUTION SALES category

Ag inputs distribution and sales

1. “Distribution”, “sales”, “retail”, “wholesale”, “supply”, “provision” (but <u>not</u> “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 feed, often in combination with PROCESSING category, if company also manufactures or produces the feed, which is often grain or oilseed milling

Ag production

1. actual operation of a farm or other production operation
2. cultivation
3. production
4. often “provision of agricultural services”
5. often mentions actual commodity produced
6. in combination with MARKETING PROCESSING category if vertically integrated business, such as livestock, oil palm
7. in combination with MARKETING PROCESSING category if fresh market, such as fruit, vegetable, produce
8. in combination with MARKETING PROCESSING 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 milling
    c. oil pressing, processing
    d. cotton ginning
    e. saw mills
    f. ethanol plants
4. other fermentation, extraction, separation, purification for ingredient manufacturing; animal feed additives (often amino acids, micronutrients, etc.)
5. food manufacturing; food brand or category for broad market (i.e. national or commodity-wide); wineries; breweries; distilleries

6. farmers markets; “local” food marketing

Consumer products, services, and retail

1. explicit mention of “consumer”, “home”, “household”
2. retail
3. specific product
4. 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
6. mention of “garden”, gardening supplies, garden equipment, indoor gardening systems, if clearly for home (not for horticulture or greenhouse industry)

Unspecified

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

Table A1. Fixed effects industry category model (Equation 2)

Variable	IC.A1	IC.A2	IC.A3	IC. A4	IC. A5	IC.A6
IPO	0.073*	0.095**	0.076*	0.041	0.057	0.040
	(0.045)	(0.041)	(0.045)	(0.047)	(0.044)	(0.048)
M&A	0.013**	0.014**	0.015**	0.010	0.010*	0.011*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Price FAO	0.865***			0.484		
	(0.250)			(0.310)		
Price FAO * Dummy [2010+=1]				0.310**		
				(0.150)		
Price Soy		0.305***			0.152	
		(0.091)			(0.114)	
Price Soy * Dummy [2010+=1]					0.133**	
					(0.060)	
Price WB			1.656***			0.942
			(0.499)			(0.595)
Price WB * Dummy [2010+=1]						0.594**
						(0.271)
Crisis	-59.5**	-57.5**	-52.5*	-67.4**	-66.8**	-61.8**
	(28.332)	(28.267)	(27.906)	(28.483)	(28.451)	(28.114)
Constant	-118***	-107***	-123***	-88.1**	-77.3**	-92.1**
	(33.83)	(31.92)	(36.00)	(36.775)	(34.494)	(38.621)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.24	0.24	0.24	0.25	0.25	0.25
N	4456	456	456	456	456	456

Note: Standard errors in parenthesis. *** for 1% significance, ** for 5% and * for 10%.