Young Firms, Old Capital*

Song Ma† Justin Murfin‡ Ryan Pratt§

(*Preliminary and incomplete*)

Abstract

This paper explores the interaction of capital reallocation and entrepreneurship activities. We document a robust fact about young firm investment—that young firms are the predominant buyers of vintage capital, originally owned and seasoned by older, established firms in the same industry and county. Using a sample of transactions covering more than 70,000 models of equipment across a wide range of industries, we show this is true within firm and within machine—that is, as firms age, they transition to newer and newer machines, and as machines age, they are reallocated to younger and younger firms. This pattern is more pronounced when financial constraints are more likely to bind. Because young firms depend on older capital, which in turn tends to trade more locally than new capital, we demonstrate there are returns to local agglomeration among young and old firms. Specifically, the local supply of vintage capital provided by older firms shapes the investment choices and growth of new businesses in the same county and industry just as the existence of local new businesses facilitates machine turnover and capital adjustment in older incumbents.

JEL Classification: L26, E22, G31

Keywords: Capital Reallocation, Financial Constraints, Agglomeration, Entrepreneurship

---

* *This version*: November 13, 2019. We thank seminar participants at Chicago Booth, Duke/UNC I&E Research Conference, FDIC, Federal Reserve Bank of Philadelphia, Federal Reserve Board, GSU Conference on Financing Tangible and Intangible Capital, Junior Entrepreneurial Finance and Innovation Workshop, Kellogg, Princeton, Tilburg, Utah, and Yale. We also thank Adriano Rampini and Xinxin Wang for detailed comments. Huijun Sun provided excellent research assistance. Yale International Center for Finance provided research support. We thank Erik Gilje for generously sharing data on county-level shale oil shocks. All errors are our own.

†Yale School of Management, song.ma@yale.edu, +1 (203) 436-4687;

‡Cornell University, justin.murfin@cornell.edu, +1 (607) 255-8023;

§Brigham Young University, ryan.pratt@byu.edu, +1 (801) 422-1222.

1. Introduction

Recent work on business cycle dynamics and growth has emphasized the importance of young firms and, separately, the process of capital reallocation. Regarding the former, new firms are a significant driver of job creation during positive local demand shocks (Adelino et al., 2017) and play a large role in how aggregate shocks are propagated (Bilbiie et al., 2012; Clementi and Palazzo, 2016; Sedláček and Sterk, 2017). Meanwhile, capital reallocation—the sale of used goods to new owners—is a significant component of aggregate investment, but its dynamics are poorly understood.

In this paper, we link these two important drivers of growth via a core feature of capital reallocation in practice: that young firms are the predominant buyers of old capital seasoned by older, established firms in the same industry and county. This pattern of capital reallocation influences both young firm investment and capital replacement rates of old firms, suggesting that the co-location of local supply and demand for used capital is an important component of the returns to economic agglomeration and influences the geography of entrepreneurial growth.

Our paper begins by documenting one robust and ubiquitous empirical regularity: using more than 1.5 million transactions covering more than 70,000 models of machines used across a broad range of industries, we show that young firms deploy older capital, whereas old firms are the predominant investors in new capital. This correlation is not obviously explained by selection related to omitted machine or firm characteristics and holds within firm, within make-model, and even within a uniquely identified machine. On average, a given reallocated machine is purchased by a firm that is two years younger than its prior owner. Similar patterns emerge in separate samples covering machine tools, woodworking tools, printers, copiers, lift trucks, and machines used in logging and construction. The documented relationship is not driven by patterns particular to some small set of industries and corresponding capital. Rather, we find that it is ubiquitous across many different industries. When performing the analysis industry-by-industry (4-digit SIC level) or equipment type-by-equipment type, we find that the relationship holds strongly, both statistically and economically, in about 85% of the industries and equipment types.

Given the observed reallocation dynamic, we then ask: what features of older machines make them relatively more attractive to younger firms? Perhaps younger firms prefer older capital because of differences in technological demand relative to older firms. For example, young firms may not have the expertise to efficiently utilize the newer technology embodied in new equipment. Yet we find no obvious correlation between firm age and a model's technological age, defined as the number of years since the introduction of a given make $\times$ model, indicating that young firms do not seem to have a preference for older technology. Alternatively, the relative labor costs of young firms may be a better match for the lower utilization rates of used machines (Bond, 1983). However, when we look at equipment choice under lease contracts (as opposed to purchase), we find a significantly flatter relationship between firm age and machine age. This suggests that the pattern of old machine purchases by young firms is not driven by firm age-based differences in demand for newer or older technology.

Instead, this fact is more consistent with a finance motive described in Rampini (2019), Eisfeldt and Rampini (2007) and Eisfeldt and Rampini (2009). Rampini (2019) points out that more durable goods have higher prices and that this effect dominates their higher collateral value in a world with imperfect capital pledgeability. Consequently, more durable goods (that is, younger equipment with a longer remaining productive life) require larger down payments per unit of capital. Financially constrained (young) firms optimally choose older capital to lower upfront costs at the expense of a higher user cost, as manifest by increased down time and/or higher ongoing maintenance costs. Eisfeldt and Rampini (2009) argues that lease contracts enjoy a repossession advantage relative to loan contracts, increasing pledgeability of capital and mitigating financial constraints. As a result, machine choice by young firms may be less distorted when machines are available for lease. Again, we find weaker links between capital age and firm age in rental and leasing markets.

We further examine the link between financial constraints and the firm age/machine age relationship by exploiting time series and cross-sectional measures of financial constraints. Specifically, we use the Federal Reserve's Senior Loan Officer Survey to capture time series variation in financial constraints and use an instrument for bank branch liquidity developed in Gilje, Loutskina, and Strahan (2016) to measure geographic variation. We find that the association between firm and capital age is most evident in periods/places experiencing tighter credit.

Given the apparent natural demand for vintage capital by young firms and the established importance of young firms in economic growth, a natural question arises: how important is the available supply of used capital to entrepreneurial investment? To answer this question, we begin by showing that, while new capital (in our U.S.-based data) trades nationally, average trade distance is strongly decreasing in capital age, perhaps due to fixed shipping costs becoming an increasing proportion of machine value as a machine ages. Thus, vintage capital tends to be reallocated more locally. Motivated by this fact, we measure the availability of local vintage capital, using records of debt-financed equipment purchases from UCC filings to track the transaction history of new machine purchases within a county. After determining a useful life for each machine type, we track the aggregate latent supply of machines of a given age that would be potentially available to a given buyer in each county by quarter. Local variation within an industry-quarter comes from the interaction between the local history of new machine purchases and machine specific variation in useful life.

We then estimate a choice model of machine purchase for young and old firms based on the latent supply of local capital. We find that local supply of equipment matters for entrepreneurial investment. Conditional on a purchase being made in a given quarter, the youngest firms are significantly more sensitive to vintage capital supply as a determinant of their investment decision, and that sensitivity monotonically declines with firm age. This fact would seem to lend credence to anecdotes common among entrepreneurs about the sensitivity of early decisions to the local availability of inputs. As a prominent example, the iconic start-up Ben and Jerry's chose to make ice cream after finding a used ice cream truck and freezer for sale locally, but only after abandoning their initial plan to make bagels due to their inability to find affordable used bagel machines.[1] We also show more generally that the local supply of used equipment in a given county-industry at the time an entrepreneur starts a new firm is positively associated with both the likelihood and value of future investments.

We conclude our investigation of the geographic agglomeration related to the supply and

[1] https://www.washingtonpost.com/business/on-small-business/when-we-were-small-ben-and-jerrys/2014/05/14/069b6cae-dac4-11e3-8009-71de85b9c527_story.html?utm_term=.f2b01c7b9a77

demand for used equipment by studying the investment behavior of old firms. If the supply of local vintage capital steers young firm investment, it may be natural to expect it to also shape the capital decisions of older firms. Using the start-up fraction of businesses in a county-quarter-industry as a measure of demand for used capital, we find that older firms reallocate their capital more frequently when they are co-located with younger firms in the same industry. All-in-all, our results indicate that young and old firms in a given geography enjoy a symbiotic relationship through the supply and demand of used equipment.

Our results are connected to a several distinct literatures. Most directly, we propose a key input into entrepreneurship and the investment demand of young firms. We also document a core feature of capital reallocation and its relationship to investment dynamics across the firm age spectrum. Finally, the fact that local capital supply matters may be relevant to our understanding of agglomerative forces in the urban economy.

2. Background and Data

2.1. Physical Capital Transaction Data

Our main data set covering sales and leases of new and used physical capital, produced and sold by Equipment Data Associates (EDA), comes from financing statements filed by secured lenders. The financing statements are designated as the means of documenting liens under the uniform commercial code (UCC) and are self-reported by lenders motivated by the need to stake a claim to specific pieces of collateral. In the event of a default on a secured loan in which multiple lenders report liens against the same piece of equipment, the first lender to have filed a UCC financing statement on that specific piece of equipment is given priority. Thus lenders have strong incentives to promptly report the collateral they have lent against. Financing statements are publicly available, but EDA sells cleaned and formatted versions going back to 1990. Similar data are used in Murfin and Pratt (2019) as well as Edgerton (2012).

[Insert Figure 1 About Here.]

Figure 1 shows an example UCC financing statement taken from Edgerton (2012). The statements typically contain identifying equipment characteristics, including make, model, year of manufacture, and serial number, allowing EDA to calculate the age of equipment. In addition, the statements provide information on the location of the purchaser/lessor, which EDA supplements with data on the firm industry, age, and when available, estimated number of employees and annual sales.

[Insert Table 1 About Here.]

The complete dataset includes more than 7 million observations covering more than 150,000 models of equipment, including construction equipment, copiers, lift trucks, logging equipment, and machine tools. Table 1 shows the industry distribution of the purchasing firm by Fama-French 12 industrial categorization. The "other" industry in Fama-French 12 is further decomposed into mining, construction, transportation, hotel, business service, and others. Not surprisingly, construction firms are important purchasers of the equipment in our sample, accounting for around 50% of the observations, but equipment transactions represent a wide variety of industries.

2.2. County-Level Conditions

To capture variation in the time series of credit conditions, we rely on a survey-based measure reported in the Federal Reserve Board's quarterly Senior Loan Officer Survey. The survey asks participating bank loan officers if they have tightened lending conditions relative to the prior quarter. We use the net percentage of officers reporting tightening (net of those reporting loosening standards) as a source of time series variation in credit conditions.

We also utilize a cross-sectional measure for local liquidity based on Gilje, Loutskina, and Strahan (2016) that traces deposit shocks due to shale oil discoveries across the branch network of banks receiving large dollar inflows related to shale discoveries. We use data from 2000 to 2010 provided by Gilje, Loutskina, and Strahan (2016) capturing the timing and magnitude of major shale discoveries in seven states: Arkansas, Louisiana, North Dakota, Oklahoma, Pennsylvania, Texas, and West Virginia. For each bank with a branch in the county receiving a windfall, the liquidity measure allocates a proportional fraction of the shock, captured using the number of wells discovered, to active banks based on their fraction of total deposits held in a windfall county. This generates a bank-quarter level variable which we average at the county-quarter in non-windfall counties using the weight of those banks in the county. Formally, the variable *Shale Shock* is defined as

$$ShaleShock_{c,t} = \sum_{b \in B(c)} BankWeight_{b,c,t} \times \sum_{c \in C} BankWeight_{b,c,t} \times BankShare_{b,c,t} \times W_{c,t}. \quad (1)$$

$W_{c,t}$ is the number of oil wells that have been discovered in county c by year t; $BankShare_{b,c,t}$ is the fraction of deposits that bank b holds in county c in year t as a fraction of total deposit in that county-year; and $BankWeight_{b,c,t}$ is the fraction of deposits that bank b holds in county c in year t as a fraction of total deposits in that bank-year. Ideally, the measure will allow us to capture cross-sectional variation in local lending conditions generated by predetermined geography of bank branch networks, while avoiding the demand effects of local economic conditions associated directly with a shale discovery.

Finally, because the link between firm age and investment has implications for how old firms will behave when they co-locate with younger firms, we require a measure of the local age distribution of firms at the industry level. Here we turn to employment data from the U.S. Census Quarterly Workforce Indicators (QWI) to compute total employment by firm age and by county. The QWI is derived from the Longitudinal Employer-Household Dynamics (LEHD) program at the Census Bureau and provides total employment in the private sector tabulated for five firm age categories—start-ups (0–1 year-olds), 2–3 year-olds, 4–5 year-olds, 6–10 year-olds, and firms 11 years old or older. The totals are provided by county, quarter, and industry, where industry is defined at the two-digit National American Industry Classification System (NAICS) level.

2.3. Summary Statistics

Table 2 reports summary statistics for equipment transactions included in the UCC data. We focus on the sample for which we observe firm-level characteristics, most importantly the age of the buyer. The mean (median) age of a machine in the UCC transaction data is four years (one year). The mean (median) firm age in our sample is by 22 (15) years, with 25% of all transactions involving firms less than six years old. The average machine in our sample had an estimated value at the time of acquisition of roughly $80k, while the 25th and 75th percentiles of equipment value are $25k and $102k.

[Insert Table 2 About Here.]

3. The Relation Between Firm Age and Capital Age

3.1. Univariate Analysis

The first contribution of the paper is to document the relation between capital age and firm age, and in particular, its robustness and consistency across markets.

Our analysis begins with a univariate illustration of how firms use different aged machines over their life cycle, and conversely, how machines are reallocated across the firm age distribution over time. In Figure 2, we plot the average age of machines purchased by firms across different age groups (1 to 10 years old), as well as the 95% confidence interval.

[Insert Figure 2 About Here.]

Newly born firms purchase machines that are on average 5.5 years old. Older firms purchase younger machines—1-year old firms' purchase 5-year old capital on average, and this number drops to 4.2 years old for firms that are 10 years old. The confidence intervals suggest that the declining pattern is not only economically meaningful but also statistically significant. The pattern, meanwhile, captures more than just the distinction between purchasing new vs. used capital. Even within the subsample of used machine transactions, it remains true that younger firms buy relatively older capital than their more seasoned counterparts, suggesting a continuous reallocation of capital to different types of firms as the capital ages.

Of course, the relationship depicted in Figure 2 may be confounded by sample selection biases arising from the changing composition of firms. Mechanically, the observations within the later age groups condition on the survival and investment decisions of continuing firms. Moreover, large differences in the distribution of age across industry, geography, and potentially a host of unobservable firm characteristics leave the plot open to interpretation. For example, a simple F-test trivially rejects equality of the industry distribution across the age buckets. Meanwhile, firms that purchase copiers are on average 24 years older than the mean firm buying construction equipment. Yet the average construction equipment transaction involves a machine that is 7.5 times older than the average copier transaction.

To visually isolate the pattern net of any selection effects driven by unobserved firm heterogeneity correlated with age, we focus on a balanced sample of the same set of firms as they acquire capital over time. In Figure 3, we limit the sample to firms that have at least 10 transaction records and track the age of machines each firm purchases as time passes. By construction each transaction number bin contains one observation each from the same set of 3,902 firms, eliminating any differences in firm composition. Moreover, this also allows us to sidestep measurement error in firm age and focus on exogenous variation due to the passage of time.

[Insert Figure 3 About Here.]

Figure 3 presents this within-firm result. On average a firm's first capital purchase involves a machine that is 5.25 years old, closely mapping to the average age of equipment purchased by newly born firms in Figure 2 (5.5 years). By the time firms are purchasing their sixth piece of equipment, the average equipment age has fallen to 3.6 years old. The decrease in machine age over the first few transactions is particularly notable, suggesting important effects near the time of firm establishment.

[Insert Figure 4 About Here.]

Finally, the documented relationship is not driven by patterns particular to some small set of industries and corresponding capital. Rather, we find that it is ubiquitous across many different industries. In Figure 4, we plot the histogram of the industry-by-industry (4-digit SIC level) β coefficients from the regression of firm age on machine age. The coefficients that are statistically significant at the 1% level are reported in white, those that are statistically significant at the 10% level are reported in light gray, and those that are insignificant at the 10% level are reported in dark gray. Across 169 industries, we find that this relationship of young firms, old capital holds at the 1% level for 131 industries and at the 10% level for 142 industries. Figure 5 shows the results from the same exercise done at the equipment type rather than industry level. Again, we see that the firm age-machine age relationship is prevalent across a wide variety of machines. Of the 115 equipment types in our data, the young firms, old capital relationship holds at the 1% level for 92 types and at the 10% level for 97 types.

[Insert Figure 5 About Here.]

3.2. Firm Age and Capital Age Regression Results

While the figures suggest a robust pattern that goes beyond industry or equipment type effects, Table 3 allows us to flexibly explore the relationship and its sensitivity to conditioning out confounding machine or firm characteristics. In these regressions, each transaction is indexed by the machine (i), purchasing firm (f), transaction year-quarter (t), and machine type or machine make-model (m):

$$\log(1 + Machine\ Age)_{i,f,t,m} = \beta \times \log(1 + Firm\ Age)_{f,t} + \delta_{FE} + \varepsilon. \tag{2}$$

Both machine age and firm age are measure as the logarithm of 1+age. Since we are limited by the observable characteristics of machines and the buyer, we sequentially incorporate a system of fixed effects, which we discuss below.

[Insert Table 3 About Here.]

In column (1), we control for year-quarter and buyer industry (3-digit SIC code) fixed effects. In this way, we remove the effect of time trends as well as time-invariant industry-level correlation between firm age and machine age. We find that the coefficient is negative and significant. The economic magnitude, –0.100, suggests that an approximate doubling of firm age results in a 10% decrease in the age of equipment acquired.

Column (2) again uses year-quarter fixed effects but replaces the industry fixed effects with firm-level fixed effects, mirroring the within-firm plot in Figure 4. We find that the negative relation between firm age and machine age is still statistically significant and economically large. Column (3) controls for year-quarter fixed effects, industry fixed effects, and machine type fixed effects. Machine types are correlated with but different from industry categorizations and broadly describe the machine's function, but not necessarily its size or power. For example, all black and white copiers comprise one machine type and all color copiers comprise another. If young firms and old firms are matched to different types of assets that have different depreciation dynamics, our results could simply be picking up this firm-asset matching outcome. The result in column (3), with an economically large and statistically significant coefficient, suggests that this endogenous matching does not explain the results. Column (4) replaces the machine type fixed effects with fixed effects at the machine make-model level. In this way, we can control for a similar matching issue in the capital purchase process as in column (3) but at the make-model level. Indeed, if different-aged firms are matched to make-models with different characteristics such as durability or the level of technology, one would worry that the estimation is picking up that matching. However, column (4) indicates that the make-model fixed effects do not explain the results, either.

Column (5) pushes the analysis to its natural limit by incorporating machine-level fixed effects, focusing the variation within exactly the same underlying asset, where the machine is identified using make-model-serial number. This evidence most clearly depicts the pattern of reallocation at the heart of the paper: machines are originally purchased and seasoned by mature firms and are then serially reallocated to younger and younger entrants over time. While the evidence from previous columns might have suggested this pattern of trade, absent the ability to actually track a given piece of equipment over time, it would be impossible to rule out variation in machine characteristics jointly driving 1) differences in demand across the firm age distribution and 2) the useful life of the machine or the timing of its turnover.

Meanwhile, the variation in owner age as a machine is traded is notable. Among the machines that we can follow, the average difference in age between the seller and buyer is 2.4 years—the owner age shrinks by 13% with each reallocation. Of course these numbers vary by industry. Woodworking tools are reallocated to a buyer that is six years younger on average than the previous owner. The difference is 5.1 years for logging tools and three years for construction equipment. Printers, copiers, and machine tools show the smallest differences in user age as the machine trades at just 2.5, 1.4, and 0.5 years, respectively, although the sign is the same in every major equipment category. In brief, older sellers pass equipment to younger buyers.

In unreported results we extend the regressions by including firm size measures in the regressions. Firm size is measured using both the amount of sales and the total employment. To separate the effects of age and size is particularly important given the recent research on the independent influences of age and size in firm behavior (Haltiwanger, Jarmin, and Miranda, 2013; Adelino, Ma, and Robinson, 2017). Not surprisingly, and consistent with Eisfeldt and Rampini (2007), larger firms purchase younger machines, and the economic magnitudes are large. However, even after controlling for firm size, firm age still plays an important role in capital investment decisions. Regrettably, coverage of firm size is only captured once in the database (i.e. we do not observe changes in firm size over time) and not for all firms, limiting our ability analyze this variation.

3.3. Economic Mechanisms

Why do young firms use older capital? Theory provides two natural sets of explanations. The first draws on the role of financial constraints in firm capital investment choices. Among others, Eisfeldt and Rampini (2007) and Rampini (2019) argue that used capital should be more attractive to financially constrained firms since they are more willing to exchange higher maintenance costs in the future for a lower down payment requirement today. A second class of explanations involve technological preferences. New technology, though relatively more productive, involves technological risks (e.g. constant updates and revisions, employee training, restructuring production lines, etc.). The effective risk aversion of young firms may guide them to older and proven technologies.

We begin by exploring the role of financial constraints. If financial constraints facing young firms dictate their choice of older equipment, we expect the firm age-machine age relationship to flatten in periods/locations with relatively easy access to credit. To test this, we construct two different indicators of credit conditions. The first is a time series measure based on the Federal Reserve Board's Senior Loan Officer Survey. The survey asks loan officers if they have tightened lending standards over the past quarter. We capture the net percentage reporting tightening (net of those reporting loosening). The second measure captures county-by-quarter variation in bank liquidity driven by deposit windfalls in distant branches of local banks. We follow Gilje, Loutskina, and Strahan (2016) in constructing the bank liquidity shock due to exposure to shale oil discoveries. We then aggregate at the county-quarter level to come up with cross-sectional geographic variation. For both measures of credit conditions, we characterize loose credit as a dummy for above median values of either the change in survey-reported credit conditions or the size of the measured shale-driven liquidity shock. We then estimate the following model:

$$\begin{aligned}\log(1+Machine\ Age)_{i,f,t} = \delta_{FE} + \beta \times \log(1+Firm\ Age)_{f,t} \\ + \beta' \times \log(1+Firm\ Age)_{f,t} \times Credit_{i,f,t} + \varepsilon_{i,f,t}.\end{aligned} \tag{3}$$

Subscript i indexes an individual transaction, f indexes the buyer firm, and t is the year-quarter of the transaction. *Credit* is a dummy variable set equal to one when the county-quarter or quarter had relatively easy credit conditions. The coefficient β' picks up any attenuating effects on the firm age-machine age relationship due to the availability of credit.

[Insert Table 4 About Here.]

The results are reported in Table 4. Columns (1) and (2) use the shale shock indicator for credit conditions, while columns (3) and (4) use the survey-based measure. Each column includes year-quarter and industry fixed effects, while columns (2) and (4) also include machine make-model fixed effects. Across the four specifications, we find that young firms' preference for old capital is strongest when credit is tight, suggesting a prominent role for financial constraints in the allocation of older capital.

Next, we turn our attention to the form of the financing contract. Though more than 70% of the transactions in our data involve loans for equipment purchase, there are also transactions involving leased equipment. While leases and loans share similar economic characteristics, Eisfeldt and Rampini (2009) argue that an important distinction arises from the difference in legal ownership. In particular, because the lessor maintains legal ownership, leased equipment is easier to repossess in the event of default. This feature increases the pledgeability of leased equipment, which in turn lowers down payment requirements and eases financial constraints. Constrained borrowers, then, may choose to lease relatively newer equipment rather than purchasing older equipment.

We test this prediction by estimating the following regression:

$$\begin{aligned}\log(1 + Machine\ Age)_{i,f,t} = \delta_{FE} + \beta \times \log(1 + Firm\ Age)_{f,t} \\ + \beta' \times \log(1 + Firm\ Age)_{f,t} \times Lease_{i,f,t} + \varepsilon_{i,f,t},\end{aligned} \tag{4}$$

where the dummy *Leasing* is set equal to one for transactions involving leased equipment.

The results are reported in Table 5. Each column includes year-quarter and industry fixed effects, while column (2) adds machine make-model fixed effects. In each specification, we find that the relationship between firm age and machine age is significantly attenuated among leased equipment. While the interpretation of the interaction term is muddled by the non-random assignment of leasing vs. owning, we interpret this result as being consistent with leasing helping to relax young firms' financial constraints.

[Insert Table 5 About Here.]

Meanwhile, comparing the effect size across lease and purchase decisions may also speak to the role of technological explanations for young firms' preference for old capital. If the correlation is driven by differential demand for technology, then young firms would seek out older equipment regardless of the form of financing. Yet our finding that young firms deploy much newer equipment when leasing than they do when purchasing poses a challenge to interpretations focused on young firms matching to older technology.

While the results in Table 5 are more consistent with the financial constraints channel, in Table 6 we attempt to more directly test the technology matching channel. To do so, we distinguish between two firm decisions: 1) the choice between purchasing an old vs. a young machine *model*, and 2) holding the model fixed, the choice between purchasing an old vs. young *machine*. A clean test of technological preference will fix machine age and test if model (technological) age varies with firm age. To do this, we restrict the sample to the subset of transactions in which the buyer firm purchases a new machine. This allows us to fix variation in the new vs. used decision and instead focus on variation in technological age, which we measure as "model age", defined as the difference between the year of transaction and the year of model introduction. If young firms purchase old capital because of non-financial reasons such as preferring older but proven technologies, one would expect that younger firms will choose longer-established models even when buying new machines.

[Insert Table 6 About Here.]

Table 6 presents the results. We find that the economic relation between firm age and model age in this regression is both economically negligible and statistically weak.

3.4. Nonincidental Sample Selection

So far, we've avoided any discussion of sample selection—i.e., the data generating process that allows us to observe equipment acquisitions together with buyer characteristics. Because our data are generated as a result of secured debt financing with liens perfected under the uniform commercial code, exclusion from the data is not random, but instead will correlate with firms' decisions to acquire capital via cash, unsecured debt, or secured debt. A simple Heckman selection model provides a natural framework for thinking about how sample selection interacts with our findings and how, as a result, we should interpret the findings with respect the total population of equipment transactions (observed and unobserved).

Assume the following equations governing the population relationship between firm and machine age, along with the sample selection:

$$\begin{aligned} MachineAge_i &= \beta \times FirmAge_i + \epsilon_i, \\ s_i &= \gamma X_i + \upsilon_i \end{aligned} \tag{5}$$

where $MachineAge$ and $FirmAge$ are only observed conditional on $s > 0$. Conditional on observing the transaction, the OLS estimate of β will be biased if both 1) X is correlated with $FirmAge$ *and* 2) the equation errors (ϵ and υ) are correlated.

In our economic setting, s captures the firm's decision to use secured debt to finance equipment. It seems reasonable that X might include $FirmAge$ as a predictor of the decision to use secured debt, as older firms may have more latitude to finance investments out of cash. While we can't test that, it thus seems plausible that condition 1) above will hold.

The less obvious condition is whether the equation errors are correlated. In practice, this correlation will be nonzero if aspects of $MachineAge$ unrelated to $FirmAge$ also appear in the selection equation. Suppose, for example, that older machines are less likely to be financed with secured debt regardless of the age of the buyer firm. Assuming older firms are also less likely to use secured debt, then conditional on observing a financing by an older firm, it will be more likely that the machine is newer (to offset the effects of firm age in the selection equation). This could explain our findings of a correlation in sample between firm and machine age even if such a relationship did not hold for the universe of transactions.

How machine age enters the selection equation is an empirical question. While it seems likely that new machines will tend to benefit from commonplace manufacturer financing relative to used machines (Murfin and Pratt, 2019), variation in financing status across machine age among used machines is not obvious. Meanwhile, 65% of equipment transactions are for machines at least one year old, so these machines will be of most interest to us in terms of understanding the typical relationship between machine and firm age.

To estimate the sign of machine age in the selection equation, we exploit a subset of UCC filings that are flagged by the data provider as wholesale acquisitions, primarily floor-plan financing for dealer inventory. These transactions are useful if we assume that when dealers borrow against machines in inventory, those machines will subsequently be sold to retail buyers. For these machines, we can then estimate the selection equation based on equipment age to understand if machine age predicts selection into the data.

[Insert Table 7 About Here.]

In Table 7, we model the selection equation, coding $MissingSale$ as 1 if a wholesale transaction was not followed by a subsequent sale over the next year. We include a dummy for new vs. used machines as well as a non-binary age variable, allowing the new vs. used margin to impact selection differently from variation in age within used machines. The table suggests that brand new machines are more likely to be selected into our sample. However, among used machines, the relationship between age and selection is economically tiny and not distinct from zero.

Given that machine age appears to influence financing (and hence selection) only at the new vs. used margin, how should we interpret our main results? To see what the results would look like absent selection, we can re-estimate the regressions from Table 3 among used machines—the subset for which age appears unimportant for selection.

[Insert Table 8 About Here.]

Because the result of interest is a correlation such that the distinction between dependent and independent variables is immaterial, and because the regression of interest requires that we truncate machine age, Table 8 switches the order of our regressors, placing firm age as the left-hand-side variable. This avoids the estimation of more complicated models to deal with the bias associated with truncated left-hand-side variables. Consistent with selection biases being small, a comparison of the main effects in columns 1–3 and 4–6 yields little difference in effect size.

4. Vintage Capital and Local Economic Activities

The evidence above suggests one reason why young and old firms may have differential demand for old vs. new capital. We now proceed by asking what consequences this has on firm investment and capital allocation. In particular, if young firms have demand for vintage capital, and older firms are natural producers of vintage capital, then this may help explain the returns to geographic agglomeration. While a substantive literature examines the labor market returns to agglomeration and its effects, here we ask if the market for used capital can support gains to co-location among young and old firms.

For this to be true, however, a necessary condition is that capital trades locally, and in particular, that markets for capital become more and more local as capital ages. We begin by establishing this fact. Given that 1) young firms demand used capital, and 2) used capital trades locally, we then explore how this dynamic influences their investment activity and the capital decisions of older firms.

4.1. Locality of Equipment Transaction

We start by examining the geographical trading patterns of equipment transactions as machines age. We focus on the relation between the moving distance of a machine in a transaction and the machine's age, based on the following model for each transaction i in year-quarter t,

$$Distance_{i,t} = \beta \times \log(1 + Machine\ Age)_{i,t} + \delta_{FE} + \varepsilon_{i,t}. \tag{6}$$

$Machine\ Age$ is the number of years between the original manufacture date and the date of transaction. As an alternative measure to capture machine age, we count the number of transactions the machine experienced prior to i. We capture moving *Distance* in two ways—the logarithm of the distance between the buyer and the seller of a machine (in miles, to the precision of the zip code level) and a dummy variable indicating whether the transaction was between two parties in the same county. In all specifications we control for fixed effects at the level of year-quarter and industry. Importantly, we also control for fixed effects of buyer county and seller county. In this way, we eliminate the influence that may arise from county-level characteristics that could impact the geographical trading patterns—such as distance to nearby markets, market size, transportation access, etc.

[Insert Table 9 About Here.]

We report the results in Table 9. In column (1), the negative coefficient means that as a machine grows older, it travels a shorter distance from the previous owner (seller) to the new owner (buyer). In terms of economic magnitude, the coefficient −0.090 means, compared to a two-year-old machine, a ten-year-old machine will travel a distance 14% shorter. Meanwhile, in column (3), this same change will increase the probability of being sold to a same-county buyer by 2.5 percentage points, which is a 12.5% increase relative to the base rate of 20%. We control for machine make-model fixed effects in these columns.

The analysis using the number of prior trades a machine has experienced conveys the same message. Adding one more trade will decrease the travel distance by about 27.2% and increase the probability of a same-county transaction by about 20%. The effects are 2–3 times larger in columns (2) and (4), where we control for individual machine fixed effects.

4.2. Measuring Old Capital Availability

So far we have shown that vintage capital is indeed more likely to be traded locally, a necessary condition for local capital supply to matter to the local economy. Next we explore the symbiotic nature of the relationship between geographically co-located young and old firms. In particular, if young firms have natural demand for used capital, they may benefit from being located near older firms who are effectively producers of used capital. Similarly, older firms which prefer newer capital may benefit from having natural buyers of their used capital in close proximity. To examine this relationship, we consider both the impact of local used capital supply on young firm investment and the manner in which used capital demand provided by young firms shapes older firms' decisions to retain or update existing capital.

Measuring old capital availability provides a challenge. The observed transaction volume of old capital is the equilibrium outcome of both the supply and demand. As a result, using observed old capital transaction quantity to document its relation with entrepreneurial activities would face severe reverse causality problems. Even if we could accurately measure the supply of old capital at each point in time—for example, the total online listings of used capital—that measure would be problematic for our purposes as well. The number of machines on the market reflects the investment opportunities in the local area, which in turn affect its business dynamism.

Instead, we approach the problem by making use of predetermined variation in the latent supply of vintage capital based on the purchase history of new physical capital in a county, interacted with its natural aging and depreciation dynamics. Our calculation of "Old Capital Availability" begins with a quarterly flow of equipment into a local region based on the new equipment purchases tracked using the EDA data. Once a machine enters a county, we count it as part of the local supply for the remainder of its useful life. We establish useful life based on the distribution of traded machine age. Although results are robust to different choices, we assume each machine is at the end of its useful life as of the 75th percentile of machine age among used transactions of the same machine type. Once a machine reaches the end of its useful life, we exclude it from the local available supply. As an example, a brush cutter purchased by a logging company in Durham, NC in 2010 with a useful life of seven years will appear in the local supply measure until 2017.

We apply the procedure described above to every machine type, which allows us to create a measure of the total number of machines at any age category available to local businesses. We can also transform the total number of machines to total machine value by weighting each machine using its price as new. In our analysis, we focus on the old machine availability measure for equipment aged three to ten years. The lower bound captures our interest in used vintage capital. The upper bound is limited by the time span of the EDA data. We cannot capture the supply of machines that are ten years old until the eleventh year of our sample, since we need to allow ten years to pass from the observation of a new machine purchase.

4.3. Old Capital Supply and Young Firm Investment Choices

Given the latent supply of used capital, we then estimate a choice model of machine purchase. Conditional on a purchase being made in a given quarter, we build a potential choice set for that transaction consisting of all of the equipment sub-categories within the same equipment type. The underlying assumption is that a buyer's choice of equipment type is dictated by the firm's production function, but the specific sub-category chosen may be influenced by local supply. For each realized transaction, we construct a set of "pseudo deals" by pairing the buyer and all the other possible equipment sub-categories under the same equipment type. Equipment type and sub-category classifications are done by EDA. On average, each equipment type contains six sub-categories, suggesting an unconditional purchase probability of 17%. As an example, a Durham lumberjack considering buying a brush cutter in 2015 might also consider the available supply of de-limbers, fellers, and tree shears. By focusing on tools that may be reasonable substitutes for the actual tool ex-post purchased, we are able to explore the intensive margin of investment.

With the unit of observation being a potential machine purchase and the outcome of interest an indicator for whether or not a given machine was chosen, we then estimate the differential effect of used capital supply on old and young firms by estimating the model

$$I(Bought) = \beta \times \mathit{LocalSupply} \times \log(1 + \mathit{FirmAge}) + \beta' \times \mathit{LocalSupply} + \beta'' \times \log(1 + \mathit{FirmAge}) + \delta_{FE} + \varepsilon, \quad (7)$$

Of course it won't be surprising that supply affects the eventual equipment choice. Instead, our identification depends on the differential effects of the latent supply of local capital across young vs. old firms. This effect will be captured by the β coefficient in the specification (7).

[Insert Table 10 About Here.]

Table 10 presents the results. We find the youngest firms are significantly more sensitive to vintage capital supply as a determinant of their investment decision and that sensitivity monotonically declines with firm age. To interpret the economic magnitude, it is perhaps easiest to break the regression from column 1 down across firm age groups. In Figure 3, we plot the average response of equipment purchase choices to a one standard deviation change in local used capital supply across firm age categories ranging from start-ups to firms older than fifty years. The reported coefficients across age groups j are estimated from the following model:

$$I(Bought) = \beta_j \times LocalSupply + \gamma\delta_{FE} + \varepsilon, \tag{8}$$

using the same set of fixed effects from column 1. If we take the oldest firms as the control, allowing us to capture the baseline elasticity of demand with respect to used supply shocks, the response by start-ups of 8% is approximately double the response by 50-year-old firms for the same supply shock. In short, at the margin, the direction in which young firms grow appears to be sensitive to what used capital is available locally.

[Insert Figure 6 About Here.]

Note, our specifications include various levels of fixed effects, including buyer fixed effects, industry-time fixed effects, county-time fixed effects, and even equipment type-county-time fixed effects. Industry-time and county-time fixed effects ensure we are not capturing slow moving industry booms correlated with supply.[2] Equipment type-county-time fixed effects completely absorb the local supply variable; here identification comes from the prediction that young firms will respond differently relative to the old firm control group.

As discussed above, the influence of local capital supply on entrepreneurial investment hinges on the assumption that physical capital is difficult or costly to relocate. Of course, some types of equipment are bound to be easier to relocate than others, and we would expect the impact of local capital supply on new firm investment to be concentrated among those

[2]Identification around these fixed effects comes from the fact that the same machine types may be used in different industries and different machine types have differing useful lives, so a buying boom in forestry five years ago will create latent supply for brush cutters but not delimbers today.

types of machines that are most costly to relocate. To test this prediction, we classify each equipment type as local or not using its historical trading pattern. We set a dummy variable $LocalMachine$ equal to one for those machine types which have an average trading distance below the median. In column (4), we interact the effect of local old capital supply and firm age with $LocalMachine$. The results confirm that it is the supply of more local capital that most significantly influences young firm investment.

4.4. Old Capital Supply and Startup Growth

Table 10 suggests that, conditional on investing, firms' choices of equipment depend on local capital supply. In this section, we ask whether the local availability of old capital has longer run effects, allowing startup companies to grow and expand via additional capital investments in the early stage of their life cycle. The analysis is performed on a cross-sectional sample of startups that made at least one equipment purchase at entry (age zero or one). We then track the equipment purchase patterns of those firms in the next five years, and estimate the following model:

$$StartupInvestment = \beta \times LocalSupply_{county,industry,year} + \delta_{industry,year} + \delta_{county,year} + \varepsilon. \quad (9)$$

The $LocalSupply$ variable is constructed at the county-industry-year level, capturing the total amount of old equipment available to the startups in the county-industry at the time of entry. Note, this supply variable is constructed based on equipment type as in Table 10 and then mapped to the industry level based on the distribution of industries which acquire that each machine type over the entire sample. For example, if half of all tractors appear in the data as agricultural purchases and half as construction purchases, then a local supply of 20 tractors will be allocated as 10 tractors each to agricultural and construction start-ups. Combinations of industry-year and county-year fixed effects are included to absorb local and industry growth trends.

[Insert Table 11 About Here.]

Table 11 presents the results using different startup investment outcome variables. Young firms with better access to old capital are more likely to purchase additional equipment within the first five years, as shown in column (1). This result also holds at the intensive margin, as column (3) shows that the total number of subsequent purchases is also higher when local capital supply is large.

In columns (2) and (4), we follow the identification strategy from Table 10 in which we differentiated between the supply of more or less mobile capital. Here locality is defined as a dummy at the industry level based on whether or not an industry's use of the "local" machines described in Table 10 is above or below the median. We hypothesize that if the industry relies more on machines that are more local (for example, because they are more expensive to transport), subsequent young firm investment will be more influenced by local capital availability. Indeed, the effect of local vintage capital supply appears marginally stronger in industries for which capital trades more locally.

4.5. Young Firms and Incumbents' Investment Decisions

Above we have shown that young firms have a natural demand for old capital. Moreover, due to the immobility of physical capital, young firms' investment decisions are impacted by the local supply of old capital. That is, young firms benefit from the availability of used capital originally bought and seasoned by older firms in the same location. As a final step in our analysis, we examine whether older firms also benefit from the ready market for their used capital facilitated by local young firms. In particular, the existence of an active entrepreneurial sector will increase the base of potential buyers and thus the overall thickness of the used equipment market. One implication of this increased market thickness would be more frequent asset turnover (Gavazza, 2011), implying more frequent opportunities for older firms to upgrade physical capital.

Using the fraction of total employment in a county-industry pair by firms five years old or younger as a measure of demand for used capital, we study the holding period of a machine bought by an established incumbent firm i in year-quarter t as it relates to expected demand for the future used version of the same machine. That is, we estimate β from the model below:

$$Holding\ Period_{i,t} = \beta \times \%\ of\ Young\ Firms + \varepsilon_{i,t}. \tag{10}$$

Each observation in this analysis is a purchase of physical equipment conducted by an incumbent, defined as firms greater than five years old. *Holding Period* is the log number of days from the date of transaction to the date of the next transaction on the same machine. *% of Young Firms* is the percentage of employment in firms in the 0–5 year-old category in the county in the year-quarter of the original purchase. In all analyses we control for fixed effects at the level of year-quarter, industry, and county.

[Insert Table 12 About Here.]

Table 12 shows the results. In column (1), we find that older firms reallocate their capital more frequently when they are co-located with younger firms in the same industry—doubling the percentage of young firm employment in the same industry-county reduces the holding period of capital by approximately 7.6%.

In columns (2) and (3), we separately estimate the relationship between local young firm activity on equipment holding periods across different age groups of incumbent firms. We sort incumbent firms into older and younger incumbents based on the median of age in the sample. We find that the oldest incumbents are the ones most likely to reallocate their used capital more quickly in the presence of an active entrepreneurial sector.

While this result is consistent with older firms benefiting from the increased liquidity of vintage capital markets facilitated by a strong local entrepreneurial sector, a competing interpretation could be that increased competition from young firms forces incumbents to downsize. In Panel B, we test whether established firms are actually upgrading to new equipment by directly examining their purchasing behaviors.

We estimate the same specification as in Panel A, except for a change of the dependent variable. We construct a variable, *Time-to-Next-Buy*, at the level of firm by equipment type. This variable is calculated as the time (in log days) from the purchase of one type of equipment by firm i to the next purchase made by the same firm of the same type of equipment. The estimates suggest that the duration between purchases decreases significantly for incumbent firms co-located with an active entrepreneurial sector, with magnitudes comparable to the decrease in holding period. Similar to the effect on holding period, the decreased time to next machine purchase is concentrated among the oldest incumbents. Taken together, Panels

A and B of Table 12 indicate that older firms upgrade to newer capital more frequently when there are more young firms around.

Because the right hand side variable of interest in Panels A and B is calculated at the level of industry×county×year, we are limited in the fixed effects that we can use to absorb local business trends that could drive both young firm creation and old firm investment. Table 13 presents an exercise that explores variation within the level of industry×place×time by exploiting difference in the breadth of industries that use a specific machine. For example, a print shop purchasing a large format industrial printer will respond to young firm density in its own industry, while the print shop at the same point in time that purchases a color copier may benefit from young firm demand across both other print shops and business service firms. This variation then allows us to include fixed effects at the level of industry×county×year not available in A and B. To operationalize this, for each machine type, we measure the frequency with which it is purchased in all possible NAICS two digit industries. We then reconstruct the weighted average % of young firm employment across these industries, (weighted by the frequency of purchase). Table 13 shows that, even absorbing industry-place-time variation in business activity with fine fixed effects, we can see firms respond via their equipment replacement decisions to the local concentration of young firms.

[Insert Table 13 About Here.]

5. Conclusions

This paper explores the interaction of capital reallocation and entrepreneurship activities. We document a robust fact about young firm investment—that young firms are the predominant buyers of vintage capital, originally owned and seasoned by older, established firms in the same industry and commuting zone. Using a sample of transactions covering more than 70,000 models of equipment across a wide range of industries, we show this is true within firm and within machine—that is, as firms age, they transition to newer and newer machines, and as machines age, they are reallocated to younger and younger firms. This pattern is more pronounced when financial constraints are more likely to bind. Meanwhile, no such pattern appears among leased capital, limiting the appeal of technological based explanations.

Finally, because young firms depend on older capital, which in turn tends to trade more locally than new capital, we demonstrate there are returns to local agglomeration among young and old firms. Specifically, the local supply of vintage capital provided by older firms shapes the investment choices of new businesses in the same commuting zone and industry.

References

Adelino, Manuel, Song Ma, and David Robinson, 2017, Firm age, investment opportunities, and job creation, *Journal of Finance* 72, 999–1038.

Bilbiie, Florin O, Fabio Ghironi, and Marc J Melitz, 2012, Endogenous entry, product variety, and business cycles, *Journal of Political Economy* 120, 304–345.

Bond, Eric W, 1983, Trade in used equipment with heterogeneous firms, *Journal of Political Economy* 91, 688–705.

Clementi, Gian Luca, and Berardino Palazzo, 2016, Entry, exit, firm dynamics, and aggregate fluctuations, *American Economic Journal: Macroeconomics* 8, 1–41.

Edgerton, Jesse, 2012, Credit supply and business investment during the great recession: Evidence from public records of equipment financing, *Federal Reserve Bank Working Paper* .

Eisfeldt, Andrea L, and Adriano A Rampini, 2007, New or used? investment with credit constraints, *Journal of Monetary Economics* 54, 2656–2681.

Eisfeldt, Andrea L, and Adriano A Rampini, 2009, Leasing, ability to repossess, and debt capacity, *Review of Financial Studies* 22, 1621–1657.

Gavazza, Alessandro, 2011, The role of trading frictions in real asset markets, *American Economic Review* 101, 1106–43.

Gilje, Erik P, Elena Loutskina, and Philip E Strahan, 2016, Exporting liquidity: Branch banking and financial integration, *Journal of Finance* 71, 1159–1184.

Haltiwanger, John, Ron S Jarmin, and Javier Miranda, 2013, Who creates jobs? small versus large versus young, *Review of Economics and Statistics* 95, 347–361.

Murfin, Justin, and Ryan Pratt, 2019, Who finances durable goods and why it matters: Captive finance and the coase conjecture, *Journal of Finance* 74, 755–793.

Rampini, Adriano A, 2019, Financing durable assets, *American Economic Review* 109, 664–701.

Sedláček, Petr, and Vincent Sterk, 2017, The growth potential of startups over the business cycle, *American Economic Review* 107, 3182–3210.

Figure 1. Sample UCC Filings

[redacted]

File Number: 20070032485B
Date Filed: 03/30/2007 02:00 PM
Elaine F. Marshall
NC Secretary of State

UCC FINANCING STATEMENT

FOLLOW INSTRUCTIONS (front and back) CAREFULLY

A. NAME & PHONE OF CONTACT AT FILER [optional]
UCC DEPARTMENT 1-888-427-8713

B. SEND ACKNOWLEDGMENT TO: (Name and Address)
JOHN DEERE CREDIT
6400 NW 86TH STREET
P.O. BOX 6630
JOHNSTON, IA 50131

THE ABOVE SPACE IS FOR FILING OFFICE USE ONLY

1. DEBTOR'S EXACT FULL LEGAL NAME - insert only one debtor name (1a or 1b) - do not abbreviate or combine names

1a. ORGANIZATION'S NAME: LEARY BROTHERS LOGGING, INC.

OR

1b. INDIVIDUAL'S LAST NAME	FIRST NAME	MIDDLE NAME	SUFFIX

1c. MAILING ADDRESS	CITY	STATE	POSTAL CODE	COUNTRY
5059 BROWN CREEK CHURCH RD	WADESBORO	NC	28170	USA

1d. SEE INSTRUCTIONS	ADD'L INFO RE ORGANIZATION DEBTOR	1e. TYPE OF ORGANIZATION	1f. JURISDICTION OF ORGANIZATION	1g. ORGANIZATIONAL ID #, if any
		CORP	NC	0263724 ☐ NONE

2. ADDITIONAL DEBTOR'S EXACT FULL LEGAL NAME - insert only one debtor name (2a or 2b) - do not abbreviate or combine names

2a. ORGANIZATION'S NAME:

OR

2b. INDIVIDUAL'S LAST NAME	FIRST NAME	MIDDLE NAME	SUFFIX
LEARY	RACHEL		

2c. MAILING ADDRESS	CITY	STATE	POSTAL CODE	COUNTRY
5059 BROWN CREEK CHURCH RD	WADESBORO	NC	28170	USA

2d. SEE INSTRUCTIONS	ADD'L INFO RE ORGANIZATION DEBTOR	2e. TYPE OF ORGANIZATION	2f. JURISDICTION OF ORGANIZATION	2g. ORGANIZATIONAL ID #, if any
				☐ NONE

3. SECURED PARTY'S NAME (or NAME of TOTAL ASSIGNEE of ASSIGNOR S/P) - insert only one secured party name (3a or 3b)

3a. ORGANIZATION'S NAME: DEERE & COMPANY

OR

3b. INDIVIDUAL'S LAST NAME	FIRST NAME	MIDDLE NAME	SUFFIX

3c. MAILING ADDRESS	CITY	STATE	POSTAL CODE	COUNTRY
6400 NW 86TH ST	JOHNSTON	IA	50131	USA

4. This FINANCING STATEMENT covers the following collateral:

John Deere 2520 Compact Utility Tractor S/N: 208130
Bush Hog TH60 Mower S/N: -08093

together with (1) all attachments, accessories and components, repairs and improvements, (2) all accounts, general intangibles, contract rights and chattel paper relating thereto, and (3) all proceeds, thereto including, without limitation, insurance, sale, lease and rental proceeds, and proceeds of proceeds.

5. ALTERNATIVE DESIGNATION [if applicable] ☐ LESSEE/LESSOR ☐ CONSIGNEE/CONSIGNOR ☐ BAILEE/BAILOR ☐ SELLER/BUYER ☐ AG. LIEN ☐ NON-UCC FILING

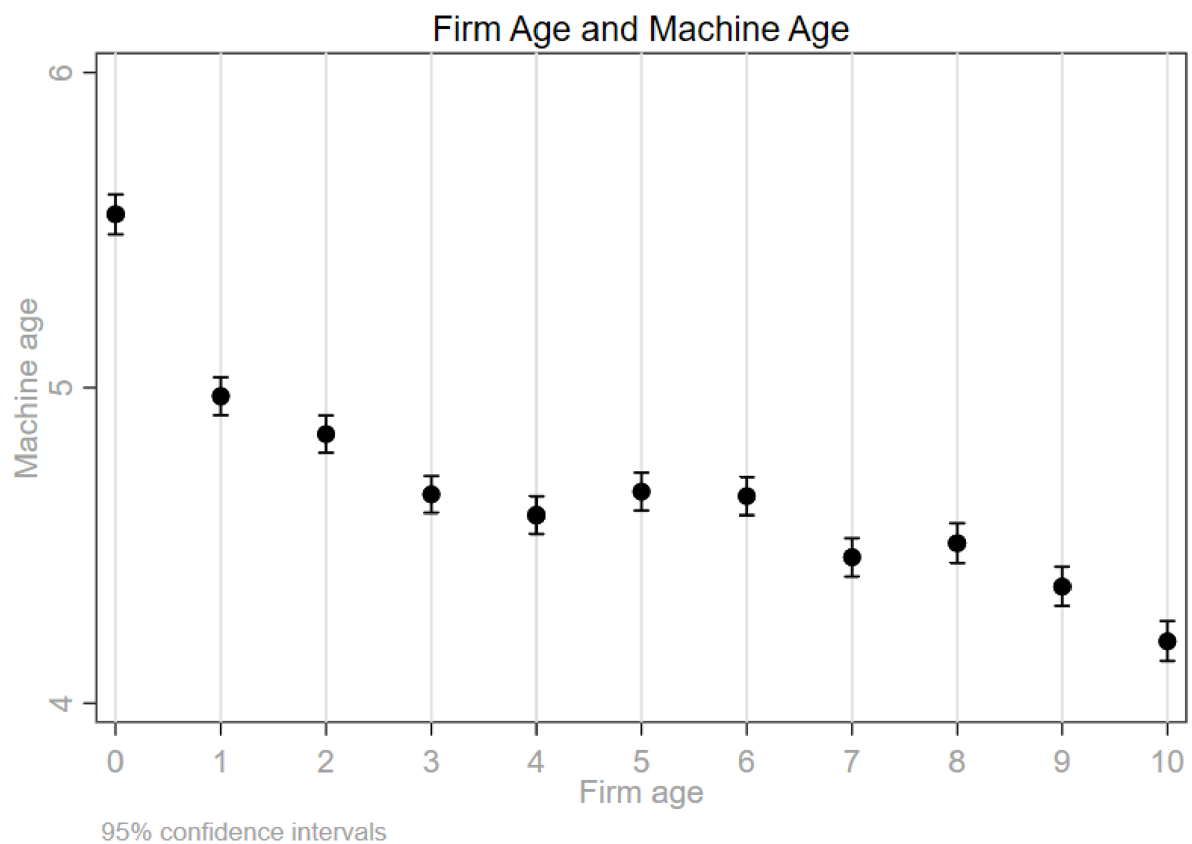
6. ☐ This FINANCING STATEMENT is to be filed [for record] (or recorded) in the REAL ESTATE RECORDS. Attach Addendum [if applicable] 7. Check to REQUEST SEARCH REPORT(S) on Debtor(s) [ADDITIONAL FEE] [optional] ☐ All Debtors ☐ Debtor 1 ☐ Debtor 2

8. OPTIONAL FILER REFERENCE DATA
SOS NC REFERENCE NUMBER: 953321 03/29/2007

FILING OFFICE COPY — UCC FINANCING STATEMENT (FORM UCC1) (REV. 05/22/02)

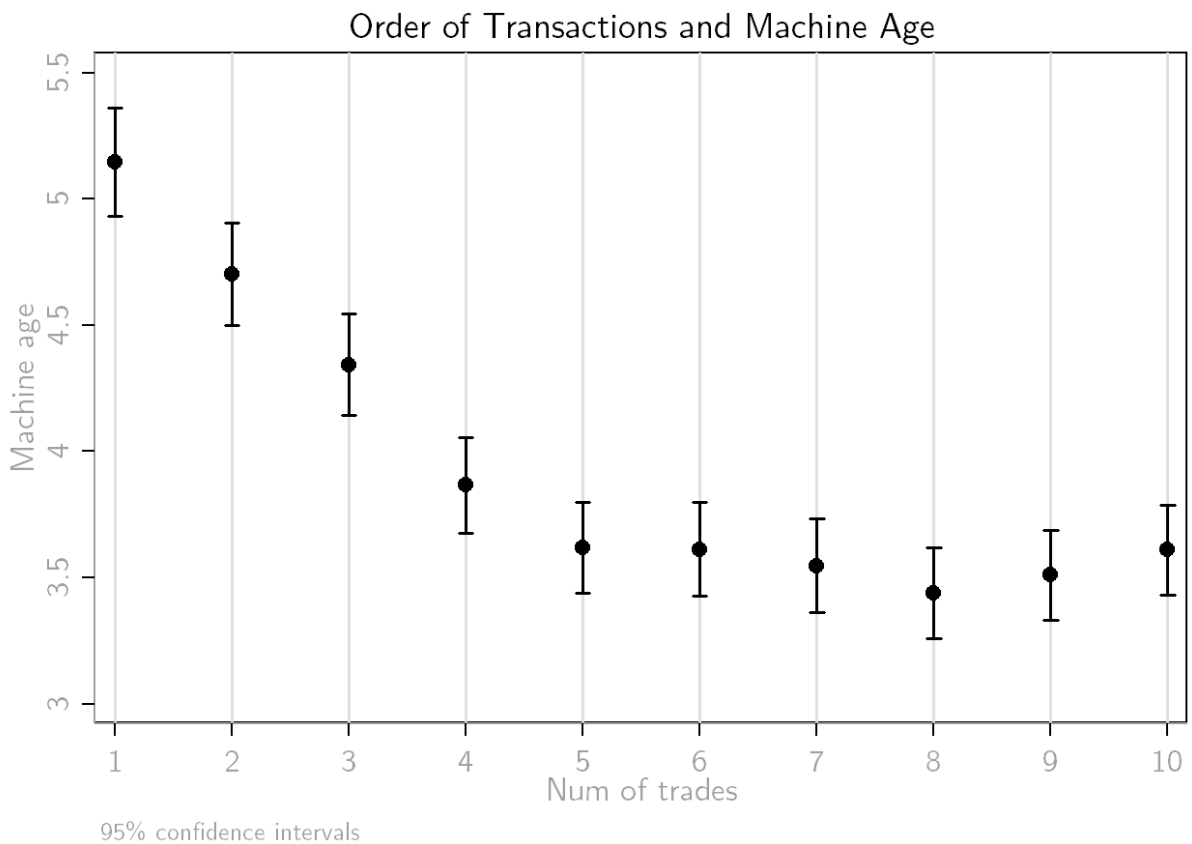
This is an example UCC filing from the state of North Carolina, provided in Edgerton (2012).

Figure 2. Firm Age and Machine Age



This graph plots the average age of machines purchased by firms across different age groups (1 to 10 years old), as well as the 95% confidence interval. The graph is produced using only transactions made by firms who enter our sample period as a new.

Figure 3. Trading Order and Machine Age



This graph plots the average age of machines purchased by firms across their own life cycles and the 95% confidence interval, by focusing on a group of firms that have at least 10 transaction record, and follow through the age of machines they purchase as the time evolves.

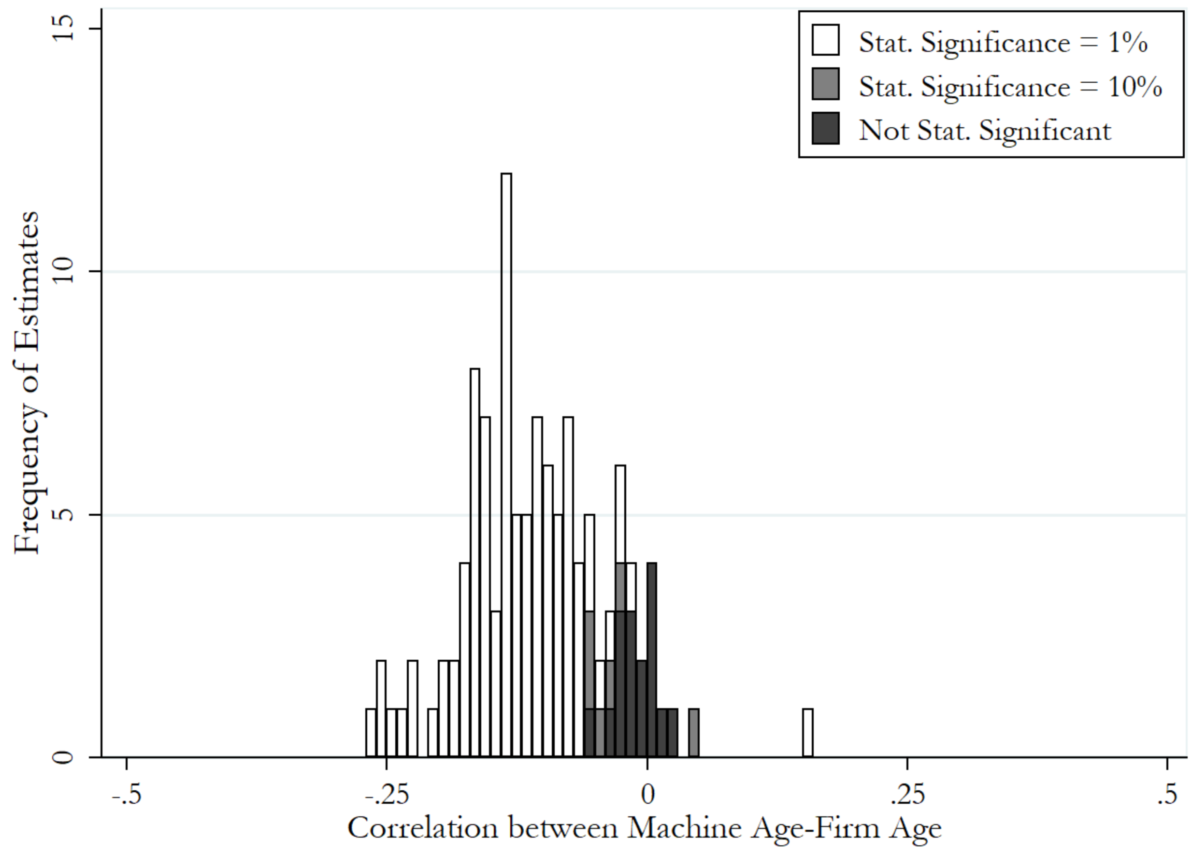
Figure 4. Firm Age and Machine Age Estimation Coefficients: By-industry Estimations

This graph plots the histogram of the industry-by-industry (4-digit SIC level) β coefficients estimated using

$$\log(1 + Machine\ Age)_{i,f,t} = \beta \times \log(1 + Firm\ Age)_{f,t} + \delta_{FE} + \varepsilon_{i,f,t}.$$

The coefficients that are statistically significant at the 1% level are reported in white, that are statistically significant only at the 10% are reported in light gray, and those that are insignificant at the 10% are reported in dark gray.

Figure 5. Firm Age and Machine Age Estimation Coefficients: By-equipment Estimations

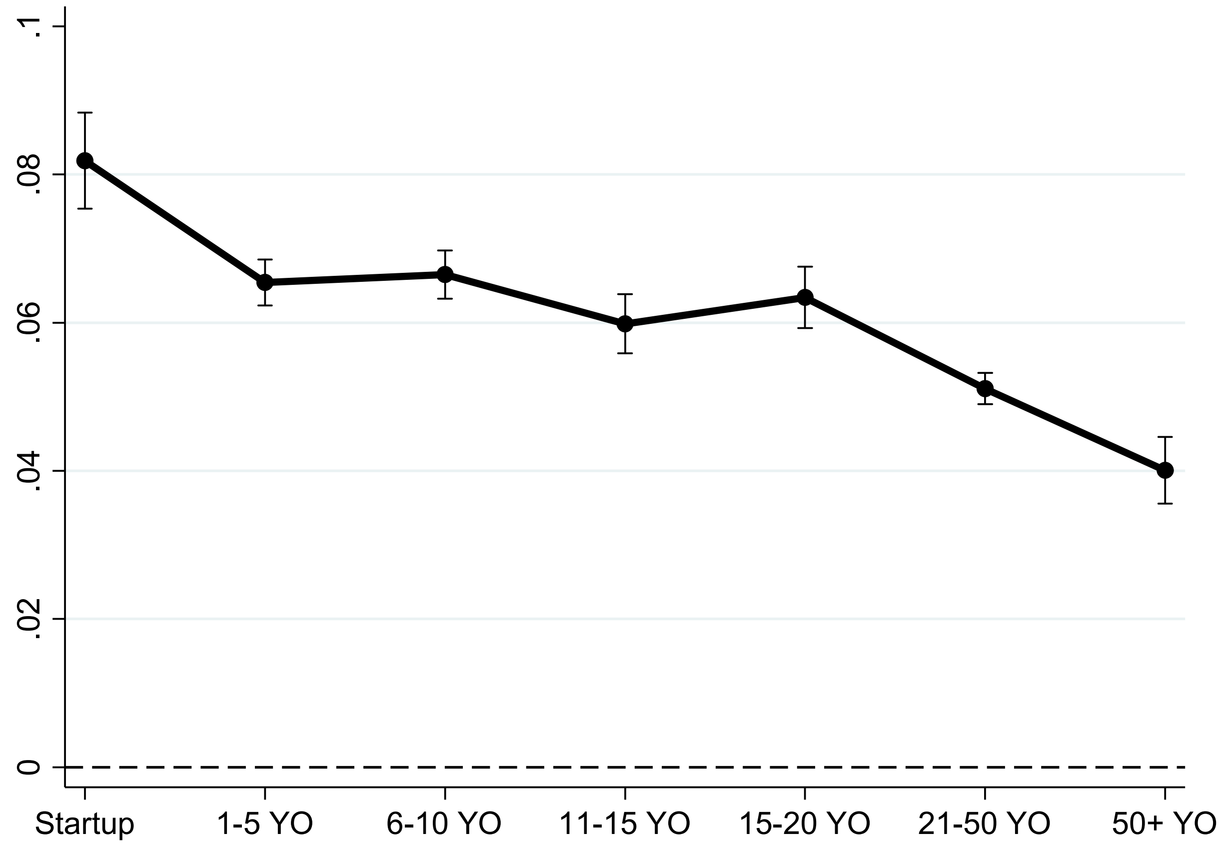


This graph plots the histogram of the equipment type-by-equipment type β coefficients estimated using

$$\log(1 + Machine\ Age)_{i,f,t} = \beta \times \log(1 + Firm\ Age)_{f,t} + \delta_{FE} + \varepsilon_{i,f,t}.$$

The coefficients that are statistically significant at the 1% level are reported in white, that are statistically significant only at the 10% are reported in light gray, and those that are insignificant at the 10% are reported in dark gray.

Figure 6. Effect of Local Old Capital Supply on Equipment Choice—By Firm Age



This figure plots the average response of equipment purchase choices on local old capital supply across different firm age groups. The reported coefficients are estimated from the following model

$$I(Bought) = \beta \times LocalSupply + \gamma\delta_{FE} + \varepsilon_i$$

using the fixed effects from column 1 of Table 9. We cut firm age groups into seven groups that are reported in the horizontal axis. 95% confidence intervals are reported for each estimated point.

Table 1
Machine Transactions Tabulated by Buyer Industries

This table provides descriptive statistics on machine transactions covered in the paper's main analysis sample. Machine transaction records are from the universe of UCC financial statement filings from 1990. The table report transactions based on buyer industries across the Fama-French 12 industries, where the "other" industry in Fama-French 12 is further decomposed to mining, construction, transportation, hotel, business service, and others.

	No of Obs	Percentage
Consumer NonDurables	168,011	11.11
Consumer Durables	21,447	1.42
Manufacturing	130,794	8.65
Oil, Gas, and Coal Extraction and Products	25,494	1.69
Chemicals and Allied Products	5,515	0.36
Business Equipment	5,521	0.37
Telephone and Television Transmission	1,987	0.13
Utilities	4,059	0.27
Wholesale, Retail	115,548	7.64
Healthcare, Medical Equipment, and Drugs	43,834	2.9
Finance	24,421	1.62
Mining	20,628	1.36
Construction	745,785	49.34
Transportation	55,129	3.65
Hotel	2,024	0.13
Business Service	31,946	2.11
Others	109,504	7.24
Total	1,511,647	100

Table 2
Summary Statistics

This table provides descriptive statistics on the equipment transactions in the sample. Machine Age is defined as the difference between the transaction date and the machine date of production. Value of equipment is defined as the price of the equipment at transaction. Firm age is the difference between the transaction date and the firm founding date. Total number of employees and annual sales are from Dun and Bradstreet.

	N	mean	sd	p25	p50	p75
Machine age	1,511,651	4	7	0	1	5
Value of equipment	1,324,253	79,908	95,540	25,218	51,867	101,766
Firm age (years)	1,511,651	22	23	6	15	29
Total number of employees	1,511,651	71	691	4	15	50
Annual sales (thousands)	1,511,651	123,553	1,713,374	430	2,107	11,600

Table 3
Firm Age and Machine Age in Equipment Transactions

This table documents the relationship between buyer firm age and machine age in equipment transactions, based on the following model,

$$\log(1 + Machine\ Age)_{i,f,t} = \beta \times \log(1 + Firm\ Age)_{f,t} + \delta_{FE} + \varepsilon_{i,f,t}.$$

Subscript i indexes an individual transaction, f indexes the buyer firm, and t is the year-quarter of the transaction. *Machine Age* is the number of years between the original manufacture date and the date of transaction, *Firm Age* is the number of years between the firm founding date and the date of transactions. We control for year-quarter fixed effects in all models. In column (1) we control for buyer firm industry fixed effects at the 3-digit SIC code level; in column (2) we control for buyer firm fixed effects; in column (3) we control for machine-type fixed effects (e.g., crawler crane); in column (4) we add fixed effects at the equipment make and model fixed level; in column (5) we add fixed effects at the level of each individual machine. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(1+Machine Age)				
Log(1+Firm Age)	-0.100***	-0.048***	-0.100***	-0.045***	-0.025***
	[0.009]	[0.010]	[0.009]	[0.004]	[0.005]
Observations	1,511,651	1,511,651	1,511,651	1,511,651	1,511,651
R-squared	0.128	0.560	0.258	0.690	0.953
Year Quarter FE	Y	Y	Y	Y	Y
Industry (SIC-3) FE	Y		Y	Y	Y
Firm FE		Y			
Machine Type FE			Y		
Machine Make-Model FE				Y	
Machine FE					Y

Table 4
Firm Age and Machine Age—The Role of Credit Conditions

This table documents the relationship between buyer firm age and machine age in equipment transactions, based on the following model,

$$\log(1+Machine\ Age)_{i,f,t} = \beta\times\log(1+Firm\ Age)_{f,t}+\beta'\times\log(1+Firm\ Age)_{f,t}\times Credit+\delta_{FE}+\varepsilon_{i,f,t}.$$

i indexes an individual transaction, f indexes the buyer firm, and t is the year-quarter of the transaction. *Machine Age* is the number of years between the original manufacture date and the date of transaction, *Firm Age* is the number of years between the firm founding date and the date of transactions. *Credit* is a categorizing variable indicating whether the county-quarter-county has high vs. low credit supply. In columns (1) and (2), *Credit* is captured using the availability of credit that are transmitted to local branches from shale oil shock through the bank internal network, following the definition of Gilje, Loutskina, and Strahan (2016). The sample size drops in this set of regressions because the shale oil shock is relevant only after 2000. In columns (3) and (4), *Credit* is from the senior loan officer survey conducted quarterly by the Federal Reserve. We use the net percentage of officers reporting loosening (net of those reporting tightening standards). The interaction of interest is between age and a dummy variable for above-median occurrences of either *Credit* variable. We control for year-quarter and industry fixed effects in all models. In columns (2) and (4) we also add fixed effects at the equipment make and model fixed level. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Log(1+Machine Age)			
Log(1+Firm Age)	-0.098***	-0.044***	-0.101***	-0.047***
	[0.009]	[0.002]	[0.008]	[0.003]
Log(1+Firm Age) x I(Shale Shock)	0.021***	0.009***		
	[0.007]	[0.004]		
Log(1+Firm Age) x I(Loose Credit)			0.006	0.011**
			[0.006]	[0.005]
Observations	693,207	693,207	1,511,651	1,511,651
R-squared	0.339	0.778	0.128	0.690
Year Quarter FE	Y	Y	Y	Y
Industry (SIC-3) FE	Y	Y	Y	Y
Machine Make-Model FE		Y		Y

Table 5
Firm Age and Machine Age—The Role of Leasing

This table documents the relationship between buyer firm age and machine age in equipment transactions, based on the following model,

$$\log(1+Machine\ Age)_{i,f,t} = \beta\times\log(1+Firm\ Age)_{f,t}+\beta'\times\log(1+Firm\ Age)_{f,t}\times Leasing+\delta_{FE}+\varepsilon_{i,f,t}.$$

Subscript i indexes an individual transaction, f indexes the buyer firm, and t is the year-quarter of the transaction. *Machine Age* is the number of years between the original manufacture date and the date of transaction, *Firm Age* is the number of years between the firm founding date and the date of transactions. This analysis includes both sales transactions and leasing transactions, and the latter is captured by an indicator variable *Leasing*. We control for year-quarter and industry fixed effects in all models. In columns (2) we also add fixed effects at the equipment make and model fixed level. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Log(1+Machine Age)	
Log(1+Firm Age)	-0.106***	-0.046***
	[0.008]	[0.004]
Log(1+Firm Age) x Leasing	0.080***	0.031***
	[0.012]	[0.004]
Leasing	-0.411***	-0.136***
	[0.042]	[0.017]
Observations	2,111,555	2,111,555
R-squared	0.166	0.679
Year Quarter FE	Y	Y
Industry (SIC-3) FE	Y	Y
Machine Make-Model FE		Y

Table 6
Firm Age and Model Age

This table documents the relationship between buyer firm age and machine age in equipment transactions, based on the following model,

$$\log(Model\ Age)_{i,f,t} = \beta \times \log(1 + Firm\ Age)_{f,t} + \delta_{FE} + \varepsilon_{i,f,t}.$$

Subscript i indexes an individual transaction, f indexes the buyer firm, and t is the year-quarter of the transaction. *Model Age* is the number of years between the first year that the specific make-model started to sell and the date of transaction, *Firm Age* is the number of years between the firm founding date and the date of transactions. We control for year-quarter and industry fixed effects in all models. In columns (2) we also add fixed effects at the equipment make and model fixed level. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Log(Model Age)	
Log(1+Firm Age)	-0.005	0.000
	[0.004]	[0.001]
Observations	827,502	827,502
R-squared	0.13	0.892
Year Quarter FE	Y	Y
Industry (SIC-3) FE	Y	Y
Machine Make-Model FE		Y

Table 7
Nonincidental Sample Selection and Machine Age

This table documents the relationship between sample inclusion/exclusion and machine age. A missing sale is defined as a machine which did not reappear as a retail sale or lease within one year of being reported as part of an equipment dealer's wholesale floorplan financing. Columns (2) and (3) include fixed effects at the machine type and machine make and model level. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Missing Sale	(1)	(2)	(3)
New Machine	-0.023***	-0.009**	-0.009
	[0.005]	[0.004]	[0.006]
ln(1+Machine Age)	-0.001	0.006	-0.001
	[0.003]	[0.004]	[0.004]
Observations	84,838	84,838	84,838
R-squared	0.002	0.007	0.003
Year FE	N	Y	Y
Machine Type FE	N	Y	N
Machine Make-Model FE	N	N	Y

Table 8
Firm Age and Machine Age Among Used Machines

Motivated by the observation that sample selection does not appear to be related to machine age within the subset of used machines, this table compares the full sample relationship between firm age and machine age with the same for the subset of used machines. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Full Sample			Used Machines		
Log(Firm Age)	(1)	(2)	(3)	(4)	(5)	(6)
Log(Machine Age)	-0.109***	-0.135***	-0.134***	-0.120***	-0.148***	-0.161***
	[0.008]	[0.005]	[0.005]	[0.010]	[0.008]	[0.007]
Observations	1,543,088	1,543,088	1,543,088	939,974	939,974	939,974
R-squared	0.106	0.084	0.145	0.083	0.071	0.140
Year FE	Y	Y	Y	Y	Y	Y
Machine Type FE	N	Y	N	N	Y	N
Machine Make-Model FE	N	N	Y	N	N	Y

Table 9
Geographical Patterns of Equipment Transactions

This table documents the relationship between the moving distance of a machine in a transact and machine age, based on the following model for each transaction i in year-quarter t,

$$Distance_{i,t} = \beta \times \log(1 + Machine\ Age)_{i,t} + \delta_{FE} + \varepsilon_{i,t}.$$

Machine Age is the number of years between the original manufacture date and the date of transaction. As an alternative measure to capture machine age, we construct the order of transactions as the number of transactions the machine went through prior to i. We capture moving *Distance* in two ways—the logarithm of the distance between the buyer and the seller of a machine (in miles) in columns (1) and (2), and an indicator variable indicating whether the transaction was between two parties in the same county in columns (3) and (4). In all analyses we control for fixed effects at the level of year-quarter, industry, buyer county, seller county. We also control for machine make-model FE in columns (1) and (3) and individual machine FE in columns (2) and (4). Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Ln(Moving Distance)		I(Same-County)	
Log(1+Machine Age)	-0.090***		0.016***	
	[0.016]		[0.003]	
Number (order of transactions)		-0.272***		0.040***
		[0.021]		[0.005]
Observations	216,864	227,134	216,864	227,134
R-squared	0.153	0.708	0.124	0.659
Year Quarter FE	Y	Y	Y	Y
Industry (SIC-3) FE	Y	Y	Y	Y
Buyer County FE	Y	Y	Y	Y
Seller County FE	Y	Y	Y	Y
Machine Make-Model FE	Y		Y	
Machine FE		Y		Y

Table 10
Equipment Purchase Choice and Local Old Capital Supply

This table studies the equipment purchase choice of firms in response to local old capital supply. For each realized transaction, we construct a set of "pseudo deals" by pairing the buyer and all the other possible equipment sub-categories under the same equipment type. With the unit of observation being a potential machine purchase, and the outcome of interest whether or not a given machine was chosen, we then estimate the differential effect of used capital supply on old and young firms under the model below:

$$Deal_{itc} = \delta_{FE} + \beta \times LocalSupply \times Log(1 + FirmAge) + \beta' \times LocalSupply + \varepsilon,$$

$Deal_{itc}$ indicates whether the pair is a realized transaction (=1) or a pseudo pair. *Local Supply* is the old capital supply calculated from the natural aging of capital. Standard errors clustered at the deal and year-quarter levels are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	I (Bought) = 1			
Log(1+Firm Age) x Old Capital Supply	-0.003***	-0.001***	-0.001**	0.001
	[0.000]	[0.000]	[0.000]	[0.001]
Log(1+Firm Age) x Old Capital Supply x Local Machine				-0.004***
				[0.001]
Log(1+Firm Age)	0.005***	0.002***	0.002*	0.003**
	[0.000]	[0.001]	[0.001]	[0.001]
Old Capital Supply	0.050***			
	[0.001]			
Observations	809,204	809,204	809,204	809,204
R-squared	0.464	0.682	0.680	0.680
Industry (SIC-3)-YearQuarter FE	Y	Y	Y	Y
Year Quarter-County FE	Y			
Machine Type FE	Y			
YearQuarter-County-Machine Type FE		Y	Y	Y
Buyer FE			Y	Y

Table 11
Old Capital Availability and Startup Investment

This table documents the relationship between startup investment behaviors and local old capital supply, based on the following model

$$StartupInvestment = \beta \times LocalSupply_{county,industry,year} + \delta_{industry,year} + \delta_{county,year} + \varepsilon.$$

Old Capital Supply is the old capital supply calculated from the natural aging of capital in the country-industry-year. *High Locality* indicates whether the industry's average equipment weight-to-value is above the sample median. In all analyses we control for fixed effects at the levels of year-industry and county-year to account for local and industry trends. *I(Buy add'l)* is a dummy indicating whether the startup bought any additional equipments after the first purchase at entry and within the first five years of the firm. *ln(Total buy)* accounts for the total number of equipment purchases within the first five years of the firm. Standard errors are clustered at the machine type level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	I(Buy add'l)		ln(Total buy)	
Old Capital Supply	0.027***	0.016***	0.037***	0.033***
	[0.003]	[0.003]	[0.003]	[0.003]
Old Capital Supply × High Locality		0.018***		0.003***
		[0.002]		[0.001]
Observations	337,194	337,194	337,194	337,194
R-squared	0.204	0.204	0.275	0.275
Fixed Effects	Industry (SIC-3)-Year, County-Year			

Table 12
Holding Period of Machines

This table documents the relationship between the holding period of a machine acquired in transaction i in year-quarter t and the % of young firms in the same county industry, based on the following model

$$Holding\ Period_{i,t} = \beta \times \%\ of\ Young\ Firms + \varepsilon_{i,t}.$$

Holding Period is the number of days between the date of a machine acquisition and its sale. *% of Young Firms* is the percentage of firms in the 0-5 year-old category in the county in the year-quarter. In all analyses we control for fixed effects at the level of year-quarter, industry, and county. We also perform the same analysis with the dependent variable being the duration until the firm purchases the next piece of equipment of the same kind. Standard errors are clustered at the machine type level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Holding Period

	(1)	(2)	(3)
		Ln(Holding Period in Days)	
	All	Older Firms ($\geq$ median)	Younger Firms (<median)
% of Young Firm	-0.076**	-0.137***	0.001
	[0.030]	[0.037]	[0.041]
Observations	183,754	98,247	77,022
R-squared	0.125	0.151	0.147
Year-Quarter FE	Y	Y	Y
County FE	Y	Y	Y
Industry FE	Y	Y	Y

Panel B: Time to Next Buy

	(1)	(2)	(3)
		Ln(Time to Next Buy)	
	All	Older Firms ($\geq$ median)	Younger Firms (<median)
% of Young Firm	-0.074***	-0.083***	0.033
	[0.020]	[0.021]	[0.035]
Observations	526,395	279,393	247,002
R-squared	0.145	0.145	0.145
Year-Quarter FE	Y	Y	Y
County FE	Y	Y	Y
Industry FE	Y	Y	Y

Table 13
Holding Period of Machines II

This table replicates Table 12, replacing the measure of % young firms with a modified measure that varies at the level of equipment type by county by year. For each machine type, we measure the frequency with which it is purchased in all possible NAICS two digit industries. We then reconstruct the weighted average % of young firms across these industries (weighted by the frequency of purchase). Specifications are otherwise similar to columns 1 in Panels A and B, except for the inclusion of industry-county-year fixed effects, and machine-industry fixed effects. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Ln(Holding Period in Days)	(2) Ln(Time to Next Buy)
% of Young Firm	-0.568***	-0.346***
	[0.063]	[0.091]
Observations	163,039	224,860
R-squared	0.334	0.303
Year-Quarter-Industry FE	Y	Y
Machine Type-Industry FE	Y	Y
Industry FE	Y	Y