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ABSTRACT

Across a broad range of equipment types and industries, we document a pattern of local capital reallocation from older firms to younger firms. Start-ups purchase a disproportionate share of old physical capital previously owned by more mature firms. The evidence is consistent with financial constraints driving differential demand for vintage capital. The local supply of used capital influences start-up entry, job creation, investment choices, and growth, particularly when capital is immobile. Conversely, incumbents accelerate capital replacement in the presence of more young firms. The evidence suggests previously undocumented benefits to co-location between old and young firms.

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1. Introduction

Recent work on business cycle dynamics and growth has emphasized the importance of young firms and, separately, the process of capital reallocation. Start-ups create the majority of new jobs in the US economy (Haltiwanger et al., 2013) and are quick to respond to local demand shocks (Adelino, Ma, and Robinson, 2017). Meanwhile, capital reallocation—for example, the sale of an existing machine from one firm to another—represents a significant component of aggregate investment (Eisfeldt and Rampini, 2006) and has been tied to large differences in cross-country development (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2017).

In this paper, we link these two important drivers of economic growth via a core feature of capital reallocation in practice: young firms are disproportionately the buyers of used physical capital seasoned by older, established firms from the same county. This pattern of local capital reallocation influences young firm creation, hiring, and investment, as well as capital replacement rates of old firms. Combined, these patterns suggest that, because of trade in vintage capital, the co-location of young and old firms may yield important benefits.

Our paper proceeds in two parts. First we document the pattern of capital reallocation from old to young and suggest some explanations. Next, taking the pattern as given, we ask how the potential for trade in old capital shapes the behavior of both young and old firms.

To document the interaction between firm and machine age, we lean on 1.56 million transactions covering 70,000 models of machines. Across a wide range of industries and equipment types, young firms acquire older capital, whereas older firms are more likely to buy new capital. This correlation is not obviously explained by selection related to omitted machine or firm characteristics, and it 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 six years younger than its prior owner. In separate samples covering machine tools, woodworking tools, printers, copiers, lift trucks, and machines used in logging and construction, the relationship between firm and machine age is both statistically and economically significant in more than 80 percent of industries and machine types. We also consider the effects of endogenous selection into our data and find limited evidence that this contributes to the relationship.

Given the observed reallocation dynamic, what features of older machines make them relatively attractive to younger firms? We find evidence consistent with a finance motive described in Eisfeldt and Rampini (2007) and Rampini (2019). 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 (in our case, younger equipment with a longer remaining productive life) require larger down payments per unit of capital. Young, financially constrained firms may optimally choose older capital to lower upfront costs at the expense of a higher future user cost. Consistent with this theory, Benmelech and Bergman (2011) find airlines in countries with stronger creditor protections, and hence more credit availability, invest in newer vintages of aircraft for their fleets.

To evaluate the extent to which financial constraints facing young firms explain the link between firm and equipment age, we exploit cross-county measures of financial constraints using an instrument for bank branch liquidity developed in Gilje, Loutskina, and Strahan (2016). We find that the association between firm and capital age is strongest in periods/places experiencing tighter credit. Related, Eisfeldt and Rampini (2009) argue 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, consistent with a financial motive, we find weaker links between capital age and firm age in rental and leasing markets. In contrast, our evidence does not seem to support theories based on young firms having different technological demand relative to older firms (Bond, 1983).

The suggestion of gains from trade across young and old firms motivates the second section of the paper, which asks how the availability of used capital facing young firms affects entrepreneurial activity. In particular, because used machine trade is largely a local activity—a fact which we document by tracking individual machine reallocation—we create a measure of local vintage capital availability based on the history of new machine transactions within a county. The history of new purchases from k years ago in county c provides a measure of the latent supply of k-year-old used machines potentially available in county c today. For example, 100 new machine purchases in Durham, NC in 2000 provides a measure

of the five-year-old machine supply for Durham in 2005. Using this measure, we investigate how variation in local vintage capital (aged five-to-ten years) affects young firm investment, hiring, and formation.

Of course, the latent supply of vintage capital may be correlated with firm dynamics for a variety of reasons. For example, long-lasting industry booms that fueled capital purchases five years ago may continue to shape investment today for reasons unrelated to machine reallocation. We lean on variation in firm and capital characteristics across three key dimensions in an effort to distinguish causal effects of the used capital market on start-ups from competing explanations.

First, motivated by the documented demand of young firms for old capital, we benchmark young firms' sensitivity to local used capital supply against that of older firms in the same area and industry. Second, we exploit variation in capital mobility determined by the physical characteristics of machines—in particular, the propensity for machines with a high weight-to-value ratio to transact more locally. If local capital availability matters, then the effect on young firm investment ought to be strongest among these machines that are most costly to relocate. In contrast, alternative hypotheses make no obvious predictions across the weight-to-value spectrum. Third, we exploit variation in the economic longevity of machines, captured as the proportion of used transactions for each equipment type that occur after five years of age. If young firm investment is driven by the availability of five-to-ten year old capital, then we should find little effect among machine types that are rarely reallocated after five years of age.

With this identification strategy in mind, we begin by showing that a more abundant supply of used machines influences start-up investment decisions at the intensive margin. Specifically, we estimate a choice model of machine purchase for young and old firms based on the latent supply of local capital for different machine types. 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 the specific type of equipment that they purchase, and that sensitivity declines with firm age. Among young firms, the impact of local vintage capital on equipment choice is concentrated among machines with high weight-to-value and long market longevity. These results 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]

The Ben and Jerry's example suggests additional interesting questions. Given the success of the ultimate enterprise, we might wonder if young firms that enjoy access to local supply of used capital show long-term benefits. For example, does local capital availability predict the volume and variety of their subsequent capital investment? Does it influence firm creation and hiring in the first place? Aggregating our vintage capital measure up to the industry level, we find that young firms that make their first investment in the presence of abundant used local capital invest more in the ensuing three years, and they invest in a greater variety of equipment types than firms with less access to used capital. Perhaps surprisingly, firms with access to used capital even appear to graduate to the purchase of new equipment more quickly than firms without access. As with the results at the intensive margin of firm investment, we find differential effects for young versus old firms as well as heavy versus light and long-lived versus short-lived capital. We also find that more local vintage capital leads to higher employment in start-ups, suggesting that used capital is not substituting for labor.

If the local supply of capital seasoned by older local firms benefits start-ups, do older firms also enjoy gains from trading with their younger counterparts? In our final tests, we use the fraction of young businesses, measured by their share of industry-county-year employment, to capture potential local demand for used capital. We then compare firms' propensity to replace specific equipment based on the presence of local young-firm users of the same equipment type. Because equipment within an industry will experience differential local young-firm demand (for example, Ben and Jerry's ice cream freezer and cash register will experience differential used demand based on differences in the industries that deploy the two equipment types), our tests can absorb fixed-effects at the level of county-industry-time. Tracking the sale of equipment via serial number, we find that firms sell and replace equipment faster when the mix of local users of the capital skews towards young firms. Joint with our findings on

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[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.

young firm investment, these 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 connect us to several distinct bodies of work. Most directly, we propose a key input into entrepreneurship and the investment demand of young firms. Start-ups often have limited resources (Petersen and Rajan, 1994). As a result, young firms show distinct features when making decisions on financing (Puri and Zarutskie, 2012; Robb and Robinson, 2014), labor (Michelacci and Quadrini, 2009; Brown and Medoff, 2003; Ouimet and Zarutskie, 2014), and business focus (Ewens, Nanda, and Rhodes-Kropf, 2018). Our paper shows that young firms are also unique in their demand for capital investment, another key component in firms' production functions.

Our paper also contributes to the active debate about how financial constraints affect entrepreneurial activity. While early evidence suggested financial constraints restricted new business formation (Evans and Jovanovic, 1989), recent theory and evidence has been more mixed (Hurst and Pugsley, 2017; Hombert et al., 2020; Bellon et al., Forthcoming). In contrast to prior work that emphasized the frequency of business formation, our paper demonstrates that financial constraints impact entrepreneurial entry and investment at the intensive margin. Interacted with used capital supply, financial constraints determine which businesses form, how quickly they grow, and in what direction they choose to invest. Meanwhile, the importance of used capital supply in easing constraints facing young firms suggests it may be an important mediating variable in the relationship between local financial conditions and start-up activity.

Finally, the fact that local capital supply is associated with new firm formation and subsequent investment may also inform our view on previously documented clustering of entrepreneurial activity at the industry-location level (Glaeser et al., 2010). Our results suggest capital availability as a previously undocumented locational amenity supporting the volume and quality of entrepreneurial activity. While the net effects of co-location for incumbent firms are ambiguous, the observation that incumbent proximity to young buyers facilitates capital replacement suggests that, at a minimum, the firm-age distribution may affect reallocation costs for used capital (Gavazza, 2011a,b). Large enough benefits to improved capital reallocation might even support a novel motivation for a form of industry

agglomeration, specifically across age cohorts: minimizing capital reallocation costs.

2.   Background and Data

Our primary data source covers sales and leases of new and used physical capital. It is collected and sold by Equipment Data Associates (EDA) and is recovered 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. EDA, however, provides cleaned and formatted versions going back to 1990, supplemented with machine- and borrower-specific information. Other papers that exploit UCC financing statements include Edgerton (2012), who uses data from California to study the impact of credit supply on business investment during the Great Recession, and Murfin and Pratt (2019), who show that equipment manufacturers use captive finance arms to maintain higher secondary market prices. Gopal and Schnabl (2020) use a comprehensive set of UCC filings to show that the void left by contraction in small business lending by banks has been filled by finance companies and fintech lenders. An introduction to financing statements and the institutional background of the data can be found in Edgerton (2012) and Gopal (2019).

[**Insert Figure 1 About Here.**]

Figure 1 shows an example UCC financing statement from the North Carolina Secretary of State's website, in this case for a Vermeer SC40TX stump cutter acquired by Hoss Treeworks and Logging. A typical statement, as in this case, contains identifying equipment characteristics, including make, model, and serial number unique to a specific machine. This allows EDA to identify the manufacture year and allows us to track equipment across sequential transactions. The statements also provide information on the location of the

purchaser/lessor, which EDA supplements with information provided by Dun & Bradstreet on the firm industry and age.

The complete data set includes over 7.8 million transaction observations between 1990 and 2017 (5.3 million sales, 2.6 million leases) covering more than 220,000 models of equipment, including construction equipment, copiers, lift trucks, logging equipment, woodworking tools, and machine tools. The equipment is coded into 113 broad categories based on functionality (e.g., cranes), which are then coded into 333 detailed equipment types[2] based on their more specific characteristics (e.g., crawler crane, truck crane). For each equipment type, we hand collect from dealer and manufacturer marketing materials the specification information for the top five most popular models, through which we obtain a measure of average equipment-type weight.[3] We use the new machine purchases in this broad equipment sample to construct a measure of local equipment supply, as described in Section 4.1.

Given our goal to link equipment reallocation with local entrepreneurial activity, we also collect region-level economic variables. These include a measure of local banking liquidity using shale oil shocks, following Gilje, Loutskina, and Strahan (2016). The variable captures variation in local credit conditions by tracking, for each county-year, the exposure to shale-discovery-driven windfalls through the banking network. For local employment data, we turn to the U.S. Census Quarterly Workforce Indicators (QWI) to compute total employment by firm age and county, similar to Adelino, Ma, and Robinson (2017) and Barrot and Nanda (2019). 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 by industry and firm-age groups, allowing us to observe local start-up activity.

[Insert Table 1 About Here.]

To study the relationship between firm age and equipment age, we focus on the sample of machine purchases for which we observe both firm age and machine age. Firm age coverage is roughly 55 percent, and machine age coverage is 70 percent.[4] Additionally, we exclude

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[2]We use "equipment type" and "machine type" interchangeably throughout the paper to refer to this level of categorization.

[3]We were able to find information for 210 equipment types covering 96 percent of observations.

[4]For firms with more than one machine acquisition, we fill in firm birth years in observations where it is missing if the birth year is populated for at least one observation.

observations with missing company names (about 16 percent of observations), non-end-user buyers (equipment dealers, auctioneers, finance companies; seven percent of observations), and government-entity buyers (two percent of observations). These restrictions leave us with 1.56 million purchase observations. Panel A of Table 1 reports summary statistics. The mean (median) age of a machine in the UCC transaction data is 3.8 years (one year). The mean (median) firm age in our sample is 22.2 (16) years, with 25 percent of all transactions involving firms less than seven years old. The average machine in our sample had an estimated value at the time of acquisition of roughly $80,000, while the 25th and 75th percentiles of equipment value are $24,824 and $102,149. Panel B reports the distribution of these equipment purchases across two-digit NAICS industries benchmarked against the 2019 GDP distribution from the Bureau of Economic Analysis (BEA). Equipment transactions span a wide variety of industries, though our data overweight capital-intensive industries such as construction (most notably) and agriculture while underweighting service industries, most prominently financial services. We will discuss the implications of this sample selection for representativeness and generalizability of our results in the next section.

3.   The Relation Between Firm Age and Capital Age

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

3.1.   Univariate Analysis

Our analysis begins with a univariate illustration of how firms use different ages of 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, as well as the 95 percent confidence interval. Newly born firms purchase machines that are on average 5.6 years old. Older firms purchase younger machines—one-year-old firms purchase capital that is 4.9 years old on average, and this number drops to 3.9 years old for firms that are ten years old. The pattern captures more than just the distinction between purchasing new versus used capital. Similar patterns obtain within the subsample of used machine transactions, suggesting a continuous reallocation of

capital to different vintages of firms as capital ages (see Figure A1 in the appendix).[5]

[Insert Figure 2 About Here.]

The economic magnitude of the pattern is sizable. Consider that in the sample, a regression of machine value (per EDA's valuation estimates) on age with model and year fixed effects reveals that an additional year of machine age reduces value by \$4,374 per year. Meanwhile, the median acquisition value of a firm in its first year is \$43,289. The roughly 2.5-year change in average machine age going from a start-up to a 30-year-old firm implies a \$10,935 reduction in acquired machine value, or 25 percent of total price.

Of course, the relationship depicted in Figure 2 may be confounded by 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.[6] 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. To compare the same set of firms at each point in the plot, we limit the sample to firms that i) have transactions in at least ten different years and ii) were less than three years old at the time of their first transaction. For this set of firms, we then track the age of machines each firm purchases with each successive capital acquisition. In addition to holding firm characteristics constant, 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 5.2 years old, between the average age of equipment purchased

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[5]The relationship between firm and machine age can similarly be seen in purchase frequencies, as shown in Table A1. The oldest decile of machines in the economy are 3.5 times as likely to be acquired by the youngest decile of firms than by the oldest decile of firms. In contrast, the same young firms buy just nine percent of new machines, 30 percent less than the volume acquired by the oldest firms.

[6]For example, 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 3.6 years older than the average copier transaction.

by zero- and by one-year-old firms in Figure 2. By the fifth year in which a firm purchases equipment, the average equipment age has fallen to 3.7 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 and different types of equipment. In Figure 4, we plot the histogram of the industry-by-industry (three-digit SIC level) and equipment-type-by-equipment-type coefficients from a regression of machine age on firm age.[7] The coefficients that are statistically significant at the one percent level are reported in white, those that are statistically significant at the 10 percent level are reported in light gray, and those that are insignificant at the 10 percent level are reported in dark gray. Across 147 industries, we find that the relationship between young firms and old capital holds at the one percent level for 115 industries and at the ten percent level for 122 industries. The relation is positive and significant at the ten percent level for only seven industries. Of the 118 equipment types with at least 1,000 observations in our data, the "young firms, old capital" relationship holds at the one percent level for 93 types and at the 10 percent level for 99 types.

3.2. Regression Results: Firm Age and Capital Age

While the figures suggest a robust pattern that goes beyond industry or equipment-type effects, Table 2 allows us to flexibly explore the relationship and its sensitivity to conditioning out confounding machine or firm characteristics. We perform the analysis on the complete set of 1.56 million equipment purchases (indexed by i) using the following model:

$$\ln(1 + MachineAge_i) = \beta \ln(1 + FirmAge_i) + \delta_{FE} + \varepsilon_i. \tag{1}$$

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[7]We require at least 1,000 machine transactions in each industry and for each equipment type. The specification is $\ln(1 + MachineAge_i) = \beta \ln(1 + FirmAge_i) + \epsilon_i$ with heteroskedasticity-robust standard errors.

In these regressions, each observation includes information on the purchasing firm, its industry and location, transaction year, machine type (e.g., compact utility tractor), and machine serial number. Both machine age and firm age are measured as the natural logarithm of one plus age.[8] Since we are limited by the observable characteristics of machines and buyers, we sequentially incorporate a system of fixed effects, which we discuss below.

[**Insert Table 2 About Here.**]

In column (1), we control for county-year and industry (three-digit SIC) fixed effects. In this way, we remove the effect of county-level time trends and industry-level variation that could drive the correlation between firm age and machine age. We find that the coefficient is negative and significant. The economic magnitude (-0.088) is large. Moving from a start-up to the mean age firm (22 years), the average age of machines decreases by 28 percent, or roughly 1.6 years, relative to the average start-up machine age of 5.6 years old. This corresponds to an approximate reduction in machine value (using EDA estimates) of $7,000, or 16 percent of median acquisition value for start-ups in the sample.

Column (2) adds 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 (2) is statistically indistinguishable from that in column (1), suggesting that endogenous matching doesn't explain the observed relationship between firm and machine age.

Column (3) introduces firm-level fixed effects, mirroring the within-firm plot in Figure 4. Column (4) 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 of primary interest: machines are originally purchased and seasoned by mature firms and are then serially reallocated to younger and younger entrants over time. Among

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[8]In Appendix Table A2, we show that the results in Table 2 are qualitatively and quantitatively similar if we transform the age variables using the inverse hyperbolic sine operator.

the machines that we can follow, the average difference in age between the seller and buyer is six years—the owner age shrinks by 26 percent with each reallocation. Whether we look within-firm or within-machine, the coefficient of interest remains consistent at around −0.09.

Figure 4 showed that the "young firms, old capital" relationship is pervasive across a wide range of industries. However, as discussed above, because our data come from machine acquisitions, the sample overweights capital-intensive industries. Given this sample selection, what do the estimates in Table 2 imply about the preference of young firms for old capital across the broader economy? To answer this question, we first examine the relationship between the estimated firm age-machine age elasticity and sample selection. In Appendix Table A3, we repeat the industry-by-industry estimation in Figure 4 within each two-digit NAICS industry. Though the coefficients vary in magnitude, each of the 21 industries shows a negative relationship that is significant at the one percent level. There is no obvious correlation between our sample selection and the coefficient magnitude—both the most overweighted industry (Construction) and the most underweighted industries (Financial services) sit near the median of the elasticity distribution. Service industries show up among those with the weakest "young firms, old capital" relationship (Health care, Education, Food services) and among those with the strongest (Other services; Administrative and support services; Professional, scientific and technical services). To examine what our results would look like in a representative sample, we re-estimate the specifications in columns (1) and (2) of Table 2, weighting the observations to match the distribution of 2019 GDP across two-digit NAICS sectors. The results, reported in Appendix Table A4, show coefficients that are 75 to 90 percent as large as those in Table 2. Not only is the pattern pervasive, but the magnitudes estimated in-sample are quite similar to averages across the economy as a whole.

3.3. Explanations for Firm Age-Capital Age Relation

In a frictionless world, where the user cost of capital is the sum of maintenance costs and incurred depreciation, we would expect secondary market prices of equipment to adjust such that the user cost is independent of equipment age. In this world, firms would be indifferent about the age of their capital. Why then do young firms display a preference for old capital? Theory provides two natural explanations: financing constraints faced by young firms and

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different technological preferences of young versus old firms. We explore these possibilities and find evidence supporting the former but not the latter.

Regarding financing constraints, 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 future maintenance costs and less durability for a lower down payment requirement today. Meanwhile, prior literature has argued that firm age is a strong proxy for financial constraints (Hadlock and Pierce, 2010). We test the role of financial constraints in explaining differential demand for used capital by interacting an instrument for bank liquidity with firm age. A flatter relationship between firm age and machine age in times/places with easier access to credit would be evidence that financing constraints play an important role. Following Gilje, Loutskina, and Strahan (2016), we capture county-year variation in bank liquidity driven by deposit windfalls in distant branches of local banks related to shale oil discoveries.[9] We characterize better credit availability using a dummy, $ShaleShock$, which takes the value one for machine purchases that occurred in county-years with above-median values of the measured shale-driven liquidity shock. We then augment equation (1) to include an interaction between the shale shock indicator and firm age to assess the role of credit conditions in the machine age-firm age relation. Specifically, we estimate

$$
\begin{aligned}
\ln(1 + MachineAge_i) =& \beta_1 \ln(1 + FirmAge_i) + \beta_2 \ln(1 + FirmAge_i) \times ShaleShock_i \\
& + \beta_3 ShaleShock_i + \delta_{FE} + \varepsilon_i,
\end{aligned}
\tag{2}
$$

where i indexes individual machine purchases. The results are reported in Table 3 columns (1) and (2), which mirror the fixed effect structure of columns (1) and (2) from Table 2.[10] The slope of the firm age-machine age relation decreases by about 20 percent with better credit access. Figure A2 in the appendix divides the plot of machine age on firm age from Figure 2 into constrained and unconstrained regions based on the $ShaleShock$ indicator. The figure shows a level shift toward newer equipment with easier credit, with the strongest effect occurring among the youngest firms.

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[9]See Appendix Section A.1 for more details on the variable construction.

[10]The reduction in sample size relative to Table 2 is because the shale shock indicator is not defined for the entire time period.

[**Insert Table 3 About Here.**]

In columns (3) and (4), we turn our attention to the form of the financing contract. To our sample of 1.56 million machine purchases, we add the lease transactions for which we observe both machine and firm age (nearly one million observations). While leases and loans share similar economic characteristics, Eisfeldt and Rampini (2009) argue that the distinction in legal ownership results in easier repossession and therefore greater pledgeability for leased equipment, which eases financial constraints. We estimate the specification from equation (2), with the shale shock dummy replaced by an indicator for whether an individual transaction was a lease or purchase. Consistent with a financial constraints motive, we find a significantly weaker preference of young firms for older capital when they lease it. The young firms/old capital relation is about 70 percent weaker among leased capital. The results in columns (1) through (4) suggest a prominent role for financial constraints in determining the allocation of capital across the firm-age spectrum. One way in which firms release the pressure imposed by financial constraints is to substitute toward older (or toward leased) capital.

The results in columns (3) and (4) are also inconsistent with explanations rooted in young firms' technological preferences. If young firms have a preference for older, more proven technologies, we would expect that preference to manifest independently of the financing contract. In columns (5) and (6), we provide a more direct test of the technological preference explanation. We replace $MachineAge$ from the specification in equation (1) with $ModelAge$, defined as the difference between the year of the transaction and the year of model introduction:

$$\ln(1 + ModelAge_i) = \beta \ln(1 + FirmAge_i) + \delta_{FE} + \varepsilon_i. \tag{3}$$

We restrict the sample to the subset of transactions, i, in which the buyer firm purchased a new machine. This allows us to fix variation in the new versus used decision and instead focus on variation in technological age. If young firms purchase old capital because of non-financial reasons such as preferring older but proven technologies, one would expect that younger firms would choose longer-established models even when buying new machines. However, we find that the relation between firm age and model age in these regression is economically

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negligible while being relatively precisely estimated.

3.4. Nonincidental Sample Selection

Because our data are generated as a result of secured debt financing with liens perfected under the UCC, exclusion from the data is not random, but instead may correlate with firms' decisions to acquire capital via cash, unsecured debt, or secured debt. For example, older firms may be more likely to purchase with cash, and/or new machines may be collateralized more often, as firms take advantage of commonplace manufacturer financing (Murfin and Pratt, 2019). Given the right (or wrong) selection equation, the true relationship between firm and machine age could be confounded by systematic exclusion from the data of young firms buying new equipment or old firms buying old equipment.

To measure the degree to which this is a problem, we separately investigate the extent to which the UCC sample is biased in its selection of i) firms and ii) machines based on age. Note that to induce a bias consistent with Heckman (1979), factors correlated with both firm and machine age must enter into the selection equation. Regarding UCC selection on firm age, in Appendix Table A5 we report the proportion of UCC machine purchases made by firms in different firm-age groups alongside the average proportion of employment by firms in those same age groups using selection-free Census (LEHD QWI) data. We are encouraged by the similarity of the two distributions, reducing the likelihood that large UCC selection effects are biasing our data to a specific end of the firm-age distribution.

Equally important is how machine age enters the selection equation. In particular, if both old firms and old equipment were systematically excluded from the data, the unlikely observation of an old piece of equipment would be more likely to be matched to a young firm (to offset the effects of machine age in the selection equation). To estimate the sign of machine age in the selection equation, we need a sample of machines for which we can observe complete information on whether each was selected into the UCC data. We exploit a subset of UCC filings that are flagged by the data provider as wholesale acquisitions, primarily floor-plan financing for dealer inventory.[11] These transactions are useful if we assume that when dealers borrow against machines in inventory, those machines will subsequently be

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[11]These observations are excluded from the other analysis since they involve non-end-user purchasers.

sold to retail buyers. For these machines, some are followed by a subsequent UCC sale (i.e., selected), and some are not (i.e., selected out). We can then estimate the selection equation based on equipment age to understand if machine age predicts selection into the data.

We define a dummy variable, $SelectedIn$, which is equal to one when the wholesale transaction is followed by a retail sale for the same machine within one year. Figure 5 shows binned scatter plots of $SelectedIn$ against machine age. In the top figure, we control for year fixed effects and find that older machines are actually slightly more likely to be included in the sample.[12] In the event that the UCC data actually do under-sample old firms, this would indicate a selection bias working against the "young firms, old capital" result. When we add machine-type fixed effects (bottom figure), we find that the likelihood of being selected into the UCC sample is unrelated to machine age except among the oldest machines. In Appendix Table A6, we examine the relationship in Figure 5 among machines aged ten years or less (93 percent of wholesale observations) and find no evidence that older machines are less likely to be selected in.

To examine the possibility that negative selection among the oldest machines is behind our results, we re-estimate the regressions from Table 2 excluding machines older than ten years, focusing on the sample for which age appears unrelated to selection. Because the regression of interest requires that we truncate machine age, Table 4 estimates a truncated regression model to deal with the bias associated with truncated left-hand-side variables. Consistent with selection biases being small, the full-sample effects (columns (1) and (2)) are very similar to the effects excluding the oldest machines (columns (3) and (4)).

[Insert Table 4 About Here.]

4.   Old Capital and Local Entrepreneurial Activity

In the prior sections, we documented young firms' apparent demand for used capital and provided evidence of potential explanations for that fact. Going forward, we take these facts as given and proceed by asking what are the consequences of this relationship on entrepreneurship, capital investment, and growth. In particular, if young firms require used

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[12]Note that the unconditional relationship is also positive.

capital, they may benefit from being located near older firms, which serve as producers of used capital. This may shape how firms invest, conditional on entry within an industry, or even the industries that entrepreneurs choose to enter.

Several questions emerge immediately. For example, do we observe large sample variation consistent with the Ben and Jerry's anecdote in the introduction of the paper, in which a start-up's investment choice was shaped by vintage capital supply? If so, is that investment choice a neutral mutation, or does the opportunity to invest in used capital have long-term consequences for start-ups' ability to grow and expand? Finally, does used capital motivate entrepreneurial entry in the first place?

Older firms that prefer newer capital may also benefit from having natural buyers of their used capital in close proximity. This would make a strong case for the importance of used capital markets, not just to support entrepreneurship, but also to shape the investment dynamics of incumbent firms, suggesting potential gains to co-location among young and old firms.

To evaluate the questions above, we propose and test two hypotheses relating young and old firm trade in vintage capital. First, we hypothesize that the availability of local old capital will influence the nature and volume of young firm investment and start-up entry (i.e., old firms' used capital benefits young firms). Second, we test if the presence of old-capital-dependent young firms allows incumbent capital owners to upgrade capital more frequently (i.e., young firms' reliance on used capital benefits old firms).

4.1. Measuring Old Capital Availability

To begin our examination of the role of vintage capital in young firm investment, we first need a measure of the volume of old capital available to young firms. We approach this problem by making use of predetermined variation in the local history of investment in new physical capital in each county reported in the EDA data. When a firm in a given county acquires a new machine, we count that machine as part of the local supply for that equipment type in the same county going forward, giving us a measure of the number of k-year-old machines available locally based on the new acquisitions made locally k years ago.

As an example, a new brush cutter purchased by a logging company in Durham, NC in

2010 will appear in the local supply of one-year-old brush cutters in 2011, the local supply of two-year-old brush cutters in 2012, and so on. We apply this procedure to every machine type in every county-year. This provides us with a measure of the total number of a given machine type of any age available to local businesses in a given county at a given time. In our analysis, we focus on the old machine availability measure for equipment aged five-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.

Also note, we focus on acquisitions of new machines to avoid treating same-machine turnover as an increase in supply. By using variation in new machine transactions as variation in the latent supply of old machines, we also ensure a gap in timing between supply shocks and current economic activity that becomes blurry with used capital transactions (for example, the purchase of a five-year-old machine at time t may reflect variation in used capital supply, but it is also mechanically linked to investment, a key outcome measure, during the same period). Using the procedure above, we define $LocalVintageCapital\_MT$ as the number of machines aged five-to-ten years of a given machine type (MT) in a given county-year.

For some of our tests, we will be interested in the total amount of old equipment available to a firm in a particular industry, which we call $LocalVintageCapital\_SIC3$. To construct this industry-level measure, we assign the machines in $LocalVintageCapital\_MT$ to three-digit SIC industries based on the proportion of each machine type acquired by firms in each industry over the entire sample. Specifically,

$$LocalVintageCapital\_SIC3_{i,c,t} =$$
$$\sum_{m \in M} IndustryWeight_{m,i} \times LocalVintageCapital\_MT_{m,c,t} \times MachineValue_m, \quad (4)$$

where i indexes industries, c counties, t years, and m machine types, and $IndustryWeight_{m,i}$ captures the number of machines of type m acquired by firms in industry i as a proportion of the total number of machines of type m. For example, if half of all excavators appear in the data as construction-industry purchases and half as logging purchases, then we allocate a local

supply of 20 excavators as ten excavators each to construction and logging industries. In this way, the supply of used capital available to each industry reflects the distribution of machines purchased by firms in that industry throughout the sample. Because each industry's supply comprises various equipment types of different values, we multiply the number of machines of a given type by the average value (as new) for that type of machine ($MachineValue_m$). $LocalVintageCapital\_SIC3$ measures the total value of all equipment aged five-to-ten years available to a given industry in a given county-year.[13]

4.2. Geographic Constraints to Used Capital Trade

Calculating the local equipment supply to test its effects on local businesses presupposes that trade in vintage capital is predominantly local. Given the ability to track machines by way of their serial number over subsequent trades, our data provide a unique setting to test this presumption. We begin with the set of all machine purchases for which we observe machine age. Under the assumption that the closest two observed acquisitions of a machine in time represent a trade from the former owner to the new owner, we can calculate the average distance that a machine travels with each subsequent reallocation. A few novel facts emerge.

[**Insert Figure 6 About Here.**]

First, the reallocation of used capital in our broad sample of equipment types and industries is a very local activity—nearly half of the capital reallocation we observe is within 50 miles, and almost 75 percent occurs within 200 miles. Figure 6 provides a histogram documenting the full distribution of trade distance. Moreover, we find that trade in physical capital becomes increasingly local as machines age. In Panel A of Table 5, we examine the effect of machine age on reallocation distance by estimating:

$$ReallocationDistance_i = \beta EquipmentAge_i + \delta_{FE} + \varepsilon_i. \tag{5}$$

The unit of observation is an individual machine reallocation, which we infer from successive

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[13]In Table 9 we will use two-digit NAICS to define industries to conform to the LEHD data. $LocalVintageCapital\_NAICS2$ is defined in a manner exactly analogous to equation (4).

transactions on machines with the same make/model/serial number. The regressions include fixed effects for the year of the transaction, buyer industry (three-digit SIC), machine type, and buyer and seller counties (separately), allowing us to control for variation in trade activity that may relate to a location's remoteness. $ReallocationDistance$ is a placeholder for two different measures of reallocation distance. In columns (1) and (2), we use $\ln(1 + MovingDistance)$, where $MovingDistance$ is the distance (in miles) between the zip codes of the seller and the buyer. In columns (3) and (4), the dependent variable is an indicator for a same-county transaction. $EquipmentAge$ is also a placeholder for two different measures. In columns (1) and (3), we use $\ln(1 + MachineAge)$, while in columns (2) and (4) we use $n^{th}Reallocation$, which is one for the first reallocation transaction we observe on a given machine, two for the second, etc. Across all specifications, we find that older machines trade more locally. For example, in column (4), we show that one additional trade for a given machine translates into a 1.6 percentage point higher probability of being traded within the same county, which is a 6.8 percent increase from the base rate of 23.7 percent.

[**Insert Table 5 About Here.**]

4.3. Identifying Variation

Armed with a set of hypotheses about how used capital shapes young firm investment and a measure of locally available used capital, we face the remaining identification challenge. Specifically, our local vintage capital measure could correlated with outcome variables via a variety of confounding economic channels. For example, long-lasting economic booms could result in both an increase in local vintage capital and an increase in entrepreneurial activity. Alternatively, our measure of old capital availability could be serving as a lagged proxy for the availability of new capital (e.g., the presence of a local equipment dealership). In order to identify the impact of old capital availability on young firm activity as distinct from alternative hypotheses, we rely on three sources of identifying variation.

First, we exploit predetermined variation in the mobility of physical capital. The fact that older capital trades more locally is consistent with the Alchian and Allen Theorem (Alchian and Allen, 1964). Alchian and Allen noted that fixed transportation costs would lead to higher quality goods being shipped, as their higher market value results in lower proportional

shipping costs. Generalizing this observation across machine types, we would expect that those machines with the highest transportation costs relative to their market value would be most constrained to trade locally.

Appendix Figure A3 plots machine transportation costs as a function of weight, obtained from the heavy equipment shipping broker uShip. The figure shows shipping costs that are concave in weight. We proxy for absolute shipping costs using $\log(weight)$, indicating that proportional shipping costs depend on $\log(weight)/value$. To estimate relative proportional shipping costs for different equipment types, we first hand-collect machine weight from manufacturer specification sheets for the top five make/models by transaction volume for each equipment type. We then divide the log of the median weight by the median value of a new machine for each equipment type and categorize equipment types into deciles of the resulting $\log(weight)/value$ measure, with machines in higher deciles having higher proportional shipping costs.

Given its correlation with shipping costs, we expect our measure of weight-to-value ratios to provide a strong proxy for constraints to the locality of trade.[14] Panel B of Table 5 supports this expectation. We rerun the reallocation distance specifications in equation (5), replacing the dependent variable with deciles of $\log(weight)/value$.[15] The results in column (1) indicate that moving up one decile on the weight-to-value measure decreases moving distance by roughly 10 percent. Figure 7 presents a binned scatter plot of this result. The pattern is monotonic with the exception of the tenth decile, which has a moving distance between that of the eighth and ninth deciles. Column (2) of Panel B reveals that heavier machines are more likely to transact within-county. Moving from the lightest to the heaviest machines increases the probability of a within-county reallocation from 18 percent to 31 percent, an increase of 72 percent. These results confirm that the weight-to-value measure provides a strong first-stage in predicting reallocation distance.[16] For the analysis that follows, we classify the top three deciles of log(weight)-to-value as *heavy* machines, the bottom three

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[14]This concept is widely used in supply chain and logistic studies and has been recently adopted in economics research (Hummels, 2007; Barrot, Loualiche, Plosser, and Sauvagnat, 2018; Koch, Panayides, and Thomas, 2020).

[15]Note that we omit machine-type fixed effects as they would subsume the weight-to-value measure.

[16]The first-stage F-statistics for columns (1) and (2) are 29.8 and 41.2, respectively, easily exceeding conventional critical values for weak instruments.

deciles as *light* machines, and the middle four deciles as *mid-weight* machines.

[**Insert Figure 7 About Here.**]

In our tests going forward, we exploit this variation in the locality of capital trade as a means of exploring competing interpretations. If local used capital supply causally affects young firm investment, it should do so more strongly for machines constrained to trade locally because of physical characteristics like weight. In contrast, if firm investment and local used supply are co-determined by confounding economic activity, contrasting predictions for high and low weight-to-value capital supply are less obvious.

As a second source of identifying variation, we exploit differences in market longevity across machine types, where we define longevity based on the upper end of the age distribution at which a machine typically trades. To motivate this idea, note that our main measure of old capital availability focuses on machines aged five-to-ten years. However, some machine types in our data trade mostly before they are five years old. This may be because they are less durable than other types of equipment or because of characteristics which make assessing their condition difficult. Regardless of the reason, any effect of local vintage capital on young firm activity should be concentrated among machines for which there is an active market beyond age five. Machines no longer marketable by year five may then serve as a control group against which we can benchmark our results.

As a measure of market longevity, we examine the 75th percentile of machine age among all used transactions for each equipment type. If the 75th percentile occurs before age five, we classify the equipment type as *short-lived*; otherwise, we classify it as *long-lived*.[17] One caveat is in order. Most equipment types in our sample have robust used markets beyond five years. Only 13.3 percent of equipment types are classified as short-lived, which limits the amount of variation we have to exploit. It is also worth noting that the market-longevity measure has little relationship with the weight-to-value measure. The average weight-to-value decile among short-lived types is 7.0, while the average among long-lived types is 5.3, indicating slightly negative correlation across the two measures.

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[17]In tests that use variation at the equipment category level (Table 6 and Table A8), we define a category as long-lived if all the machines types in that category have their 75th percentile of transaction age above five years.

While it is possible that weight-to-value and market longevity attributes may match to some unobservable firm or industry characteristics, two noteworthy features of the data suggest that our categorization of machines is not strongly related to industry classification. First, each group of equipment is utilized across a broad set of industries. Within each individual group of equipment (heavy, light, long-lived, and short-lived), machine purchases are spread across at least 414 of the 424 three-digit SIC industries in our data. Second, industries that are large-scale purchasers of one group of equipment tend to be large-scale purchasers across groups. The correlation between an industry's share of heavy equipment and its share of light equipment is 0.53, while the correlation between the long-lived and short-lived shares is 0.52. These positive correlations are driven simply by the fact that some industries are more capital intensive, but nonetheless they imply that the important industries in our data are not concentrated in one group of equipment.

Appendix Table A7 provides examples of common equipment types from each group along with the modal industry that uses each type. The broad-based patterns are evident among these examples. Within each group, equipment types map to a variety of modal industries, and the same industries show up as important users of equipment across different groups (e.g., Heavy Construction, except Highway; Miscellaneous Special Trade Contractors; Industrial Machinery, NEC; and Groceries and Related Products each show up in multiple groups, in each case spanning "control" and "treatment" groups).

Finally, in addition to the weight-to-value and market longevity measures, we will also benchmark the effect of old capital supply on young firms against the effect on more mature firms (throughout the paper, when we need a binary measure of firm youth, we define "young" firms as those aged three years and younger). While a relationship between local old capital and entrepreneurial activity may be driven by confounding local economic conditions such as long-lived industry booms, it is not obvious that this would lead to differential effects on young versus mature firms. In contrast, if the presence of old capital influences firm investment directly, we would expect young firms to be more sensitive to the presence of local old capital.

4.4. Local Vintage Capital and Young Firm Investment Choice

With variation in the local supply of old machines across time, place, and machine type, we begin by examining how the supply of old machines shapes firm investment choices, conditional on an investment occurring. Returning to the example from earlier, the Durham lumberjack who bought a brush cutter in 2010 might also consider the available supply of de-limbers, fellers, and tree shears. By focusing on reasonable substitutes for the actual tool purchased, we are able to explore the intensive margin of investment type, asking how the relative availability of different physical capital influences the lumberjack's investment choice.

To answer this, we estimate a choice model of machine purchase based on variation in used capital supply.[18] For each actual machine purchase in a given county-year, we assume a potential choice set consisting of all the equipment types (e.g., brush cutter, de-limber) within the same broader equipment category (e.g., logging tools). Equipment type and category classifications are provided by EDA and defined by machine function. On average, each equipment category (containing more than one equipment type) contains 5.53 equipment types, suggesting an unconditional purchase probability of 18 percent. We test whether the availability of old equipment influences the specific choice of equipment from among alternatives in the same category by estimating:

$$
\begin{aligned}
ChosenMachine_{i,m} = & \beta_1 \ln(1 + LocalVintageCapital\_MT_{i,m}) \times Interaction_{i,m} + \\
& \beta_2 \ln(1 + LocalVintageCapital\_MT_{i,m}) + \beta_3 Interaction_{i,m} + \delta_{FE} + \varepsilon_{i,m},
\end{aligned}
\tag{6}
$$

where i indexes actual machine purchases and m indexes alternative machine types within the same category. The unit of observation is a potential machine purchase, with $ChosenMachine$ set to one for actual purchases and to zero for unchosen alternatives. $LocalVintageCapital\_MT$ varies at the equipment type-county-year level, capturing variation in the latent supply of each type of equipment.

Of course, given the localness of machine trade documented in Section 4.2, it may not be surprising that local supply affects equipment choice on average. Instead, we are interested

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[18]For the investment regressions in Tables 6–9, we begin with the set of all machine acquisitions for which we observe both firm age and company name, and we drop non-end-user and government-entity buyers.

in the differential effects of the latent supply across firm age cohorts, machine weight-to-value, and market longevity, with each of these variables taking turns in place of the generic *Interaction* in equation (6).

For example, consider two Durham County lumberjacks—one young, one old—who are both making an acquisition of forestry equipment in 2010. They are faced with the same opportunity set of equipment types but with varying levels of local capital supply. Our first hypothesis is that young firms' decisions will be more sensitive to local old capital supply, consistent with earlier findings that young firms are predisposed to acquiring older machines. Our specifications test this by estimating the sensitivity of machine choice to vintage capital supply, interacted with firm age. Regressions include fixed effects at the equipment category-county-year level (e.g., logging tools-Durham-2010) to capture the thought experiment described above while netting out slow moving industry booms or local economic trends correlated with supply. We also control for equipment-type fixed effects (e.g., brush cutter, de-limber) to absorb machine characteristics correlated with supply. Standard errors are double clustered at the industry (three-digit SIC) and county level.

Note, however, that the hypothesis that used capital supply has a causal effect on machine choice implies a larger sensitivity to supply based on age primarily for machines that are constrained to trade locally based on their higher weight-to-value and long-lived machines. Hence, consistent with our argument in Section 4.3, any observable sensitivity to equipment supply for lower weight-to-value and/or short-lived machines will give us a baseline effect against which to estimate real effects originating from local used capital trade.

[**Insert Table 6 About Here.**]

Table 6 presents the results. In column (1), we report the baseline sensitivity of all firms to the local vintage capital measure for heavy and long-lived machines. We standardize $\ln(1 + LocalVintageCapital\_MT)$ to have a mean of zero and standard deviation of one. A one-standard-deviation shift in (log) supply of a given machine type increases its odds of being chosen by roughly 0.129, compared to a sample mean of 0.18. In column (2), we compare the sensitivity to local vintage capital across the firm age spectrum. The interaction with firm age is significant and negative—as firms age, they become less sensitive to local

used capital supply. We return to discuss the economic magnitude after examining the other columns of Table 6.

While our analysis is designed to test the hypothesis that old capital availability induces young firms to adjust their investment program, an alternative interpretation introduced in Section 4.3 is that used capital supply, constructed out of a lagged measure of new capital purchases, captures a five-to-ten year lag in local industry dynamics to which young firms are simply more sensitive. Old capital availability may also simply capture a lagged proxy for access to new capital in the local area.

To identify among competing explanations for the results in columns (1) and (2), we introduce our two ancillary predictions that would follow from used equipment supply causing investment choice but not from the confounding industry dynamics described above. First, a causal effect of used capital implies that the used supply of physically heavier equipment (relative to value) will have a larger effect on young firm behavior. Second, the effects of our vintage capital measure presume a machine's ability to remain marketable for at least five years after its introduction as a new machine to the area.

Column (3) re-estimates the effects from column (2), this time focused on a control group of machines that are not long-lived and/or not heavy (i.e., the complement of our treatment group of heavy, long-lived machines in column (2)). While we continue to see a positive coefficient on $\ln(1 + LocalVintageCapital\_MT)$, the level effect is about half as large as in column (2). On one hand, the coefficient shrinkage would seem to validate our categorization of long-lived and heavy equipment. On the other, the continued positive and significant coefficient on the level of equipment supply reinforces our concerns that supply might correlate with machine choice for reasons unrelated to vintage capital trade.

However, as we move on to interpret the role of firm age as a mediating variable for supply, we find that supply effects do not appear to respond to firm age for the control group of machines. The difference in the coefficient on $\ln(1 + LocalVintageCapital\_MT) \times \ln(1 + FirmAge)$ between columns (2) and (3) is -0.004 and is significant at the one percent level. Young and old firms respond differently to vintage capital supply, but only among heavy, long-lived equipment, consistent with our preferred interpretation.

Columns (4) and (5) delve deeper into young firms' sensitivity to old capital supply. Here,

we focus attention on young firms (aged three years or less) and interact the used-capital-supply effect on choice with heavy vs. light (we exclude mid-weight machines) and long-lived vs. short-lived dummy variables. In each case, the results are consistent with the physical proximity to vintage capital shaping investment decisions of young firms, with larger effects for heavy equipment constrained to trade locally (column (4)) and smaller effects for machines that have limited used marketability after the first five years of life (column (5)). These interactions undermine a view of the findings that depends on local investment booms or the correlated access to new capital. If booms have more persistent or lagged effects on young firms, that should hold for heavy or light equipment. Yet we observe significantly differential effects. Meanwhile, if local access to new capital impacts purchase decisions, it should do so independently of machine longevity. Instead, among the youngest firms, supply effects are concentrated among machines with market longevity. Appendix Table A8 reports results including heavy vs. light and long-lived vs. short-lived interactions in the same specification, confirming the two measures capture distinct economic effects.

Figure 8 takes these three dimensions (firm age, machine weight, and longevity) into account to help visualize the differential economic magnitudes. For categories of heavy and light machines, and for short-lived and long-lived machines, we run the regression presented in column (1) across six firm age groups, ranging from start-ups to greater than 50-year-old firms. We then plot the coefficient on local vintage capital across age groups for heavy and long-lived machines against the same responses for the placebo groups (light and short-lived).

[**Insert Figure 8 About Here.**]

Several facts jump out. For light equipment and short-lived equipment, we find small effects across all firm age groups (coefficients of 0.03 and 0.05, respectively). We interpret these as baseline effects which are unlikely to relate to actual used capital trade and are thus likely attributable to confounding mechanisms described earlier. We see consistently larger vintage capital effects for all firm age groups among heavy and long-lived equipment, but in particular among the youngest firms (coefficients of 0.11 and 0.12). Taken together, comparing start-up sensitivity to used capital supply for heavy (long-lived) equipment to the baseline effects evident for light (short-lived) equipment implies that a one standard deviation

increase in (log) vintage capital supply raises the probability of a purchase by 0.08 (0.07). This is a sizable effect when compared to the unconditional probability of choosing a machine of 0.18. Controlling for the effects of alternative hypotheses, local used capital supply holds significant sway over investment choices of the youngest firms.

It is also impossible to ignore that only among heavy and long-lived equipment groups, the effect of equipment supply is (near) monotonically declining with firm age. Differential supply effects for the treatment and placebo equipment types disappear among the oldest firms, again, for which we expect minimal causal effects of used capital supply.

4.5. Local Vintage Capital and Young Firm Growth and Entry

Conditional on investing, young firms' choices of equipment depend on the supply of old capital. In this section, we investigate whether local availability of old capital has longer-run effects. Does local vintage capital simply nudge young firm investment into one of several equally profitable alternatives? Or does it have a meaningful impact on a firm's growth trajectory during its early years?

To examine this question, we focus on the sample of firms for which we observe at least one equipment acquisition during their first three years. We then estimate how local vintage capital availablity at the time of the initial acquisition shapes the subsequent investment dynamics. Specifically, we estimate the following regression:

$$\ln(1 + Investment_{1-3,i}) = \beta \ln(1 + LocalVintageCapital\_SIC3_{0,i}) + \delta_{FE} + \varepsilon_i. \quad (7)$$

$Investment_{1-3,i}$ captures investment of firm i between one and three years after the first observed acquisition measured in three different ways: the total number of machines acquired, the number of different machine types acquired, and the number of new machines acquired.[19] As described in Section 4.1, $LocalVintageCapital\_SIC3_0$ varies at the county-industry-year level and measures the total value of equipment aged five-to-ten years available to start-ups in the county-industry at the time of the initial investment (the numerical subscript denotes the timing of measurement). We standardize the main independent variable to ease the

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[19]Each outcome variable is winsorized at the 95% level to mitigate the influence of outliers. Estimated effects are slightly larger without winsorization.

interpretation of our estimates and double cluster our standard errors at the industry (SIC-3) and county levels.

[Insert Table 7 About Here.]

Table 7 presents the results. In odd columns, we include county, industry (three-digit SIC), and year fixed effects. Local business dynamics or industry trends that jointly drive investment and vintage capital supply are potential confounders in equation (7). To address this, we include county-year and industry-year fixed effects to absorb local and industry trends in even columns. With these fixed effects, the regressions compare two young firms in the same county-year (e.g., Durham, NC in 2010) but in different industries (e.g., logging versus construction) and ask whether young firms in the industry with more available vintage capital invest more in the ensuing years, after controlling for the average investment dynamics of each industry. Columns (1) and (2) show that young firms with better access to old capital when they first invest acquire more additional equipment between one and three years after their initial investment. A one-standard-deviation increase in the (log) amount of local used capital leads to a 7.6 percent increase in subsequent capital investment.

While the results in columns (1) and (2) are consistent with old capital availability facilitating survival and growth of start-ups, it is also possible that the subsequent capital investments arise as young firms need to replace their initial used-capital investment. To address this possibility, in columns (3) and (4) we examine the breadth of young firm investment, as captured by the total machine types that a young firm invests in between one and three years after its initial investment. We find a one-standard-deviation increase in the (log) local supply of used capital at the time of a young firm's initial investment leads to a 6.2 percent increase in the number of equipment types a firm invests in over the ensuing years.

In columns (5) and (6) we examine young firm investment in new (unused) equipment between one and three years after their initial equipment investment. We find that young firms subsequently invest more in new equipment when their initial investment was facilitated by a large supply of used equipment, with a one-standard-deviation increase in (log) used capital supply resulting in a 4.5 percent increase in future investment in new equipment. That is, young firms do not simply subsist off of a supply of local used capital. Instead, early

investment opportunities enhanced by available used capital help young firms graduate into investment in new capital. Taken together, the results in Table 7 suggest that firms expand more via additional capital investments during the early stages of their life-cycle when they are born in the presence of a robust supply of vintage capital.

As discussed in Section 4.3, the influence of local capital supply on entrepreneurial investment hinges on the assumption that physical capital is difficult or costly to relocate. If locally available used capital causes entrepreneurial investment, we would expect the local supply of high weight-to-value (immobile) equipment to impact new firm investment more than the local supply of lighter, more mobile equipment. Meanwhile, other potential explanations for the link between investment and vintage capital supply—for example, local industry booms with lagged effects on start-ups—offer no clear predictions regarding the differential impact of heavy versus light equipment.

To test this hypothesis, we cannot simply interact $LocalVintageCapital\_SIC3$ with a weight-to-value categorical variable as we did in Table 6, since $LocalVintageCapital\_SIC3$ is an industry-level measure that includes all equipment types. Instead, we partition $LocalVintageCapital\_SIC3$ into heavy, mid-weight, and light components. LVC_Heavy is the local, industry supply of equipment categorized as heavy in Section 4.3 (top three deciles of $log(weight)/value$) and constitutes 16.7 percent of total equipment supply on average. $LVC\_Midweight$ and LVC_Light are defined analogously and make up an average of 47.6 and 35.8 percent of total equipment, respectively.[20] We then replace the total vintage capital measure from the regressions in Table 7 with the individual components so that we can compare coefficients across these components of total vintage capital:

$$
\begin{aligned}
\ln(1 + Investment_{1-3,i}) = &\beta_h \ln(1 + LVC\_Heavy_{0,i}) + \beta_m \ln(1 + LVC\_Midweight_{0,i}) + \\
&\beta_l \ln(1 + LVC\_Light_{0,i}) + \delta_{FE} + \varepsilon_i.
\end{aligned}
\tag{8}
$$

We include county-year and industry-year fixed effects to control for potentially confounding local and industry trends. The null hypothesis in these tests is that all equipment, regardless of weight-to-value, has the same impact on future young firm investment—that is, $\beta_h = \beta_m = \beta_l$. To facilitate this comparison, each independent variable is scaled such that the interpretation

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[20]Note that $LocalVintageCapital\_SIC3 = LVC\_Heavy + LVC\_Midweight + LVC\_Light$.

of β_h (β_m, β_l) is the effect of a one-standard-deviation increase in (log) *total* equipment supply coming exclusively from additional *heavy* (*mid-weight, light*) equipment.[21]

<div align="center">

[**Insert Table 8 About Here.**]

</div>

The results are shown in Panel B of Table 8. In column (1), we find that a one-standard-deviation increase in (log) vintage capital coming from additional heavy capital increases subsequent young firm investment by 16.0 percent. For increases in equipment coming from additional medium weight-to-value capital, young firm investment increases by 11.7 percent, while investment changes by a statistically insignificant 3.2 percent with additional light capital. An F-test rejects equivalence of β_h and β_l with a p-value of 0.040. Columns (2) and (3) confirm a similar pattern for the number of machine types in which young firms invest and their investment in brand new equipment. Overall, Panel B indicates that both the depth and breadth of young-firm investment, as well as their ability to ultimately purchase brand new equipment, are enhanced particularly by the availability of immobile local capital. In each case, the impact of light equipment is close to zero, while the difference between the effect of heavy and light equipment has a p-value between two and seven percent.

In Panel C, we examine how the impact of old capital availability depends on equipment market longevity. If young firms benefit from old equipment available in used equipment markets, that benefit ought to be concentrated among the machines that actually transact after five years of age—after all, our measure of vintage capital only tracks machines five to ten years old. Conversely, any effects observed for machines that do not trade after the age of five are unlikely to be related to vintage capital effects and therefore serve as a useful control group. Note, this test helps rule out, among other explanations, that areas with ample used capital also benefit from easy access to new capital.

To test this prediction, we repeat the process described above for weight-to-value, this time partitioning *LocalVintageCapital_SIC3* into long-lived and short-lived components, as defined in Section 4.3. *LVC_LongLived* makes up 83.0 percent of total vintage capital on average, while *LVC_ShortLived* makes up 17.0 percent—most equipment has a robust used market. Across all dependent variables, only the availability of long-lived machines impacts

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[21]For the interested reader, we describe this scaling in detail in Appendix Section A.2. The same scaling applies to the results in Panel C as well as Table 9.

future young firm investment; in each case, the relationship with short-lived equipment is insignificantly negative. An F-test rejects equivalence of long- and short-lived equipment supply with p-values around 0.05 for total machines and machine types acquired. For new machine purchases, the p-value is a marginally significant 0.118, mostly due to the imprecision with which the effect of short-lived capital is estimated. In Appendix Table A9, we interact the two measures to confirm that the heavy versus light comparisons from Panel B and the long-lived versus short-lived comparisons from Panel C capture distinct economic effects. Holding equipment market longevity fixed sharpens the effect of weight-to-value, with p-values for heavy versus light equipment falling to between 0.8 and 2.1 percent. Symmetrically, holding equipment weight-to-value fixed, the p-values for long-lived versus short-lived equipment fall to between 1.5 and 3.6 percent.

Finally, we ask whether the impact of old capital supply on young firm growth and success is different than the impact on old firms. Given young firms' preference for old equipment, we would expect that young firm success is more sensitive to old capital supply. In measuring young firm success, we capture follow-on investments after an initial investment. When benchmarking against old firms, however, there is no natural first investment event. Instead, for old firms, we choose a random investment and measure the amount of additional investment one to three years after that randomly chosen investment.

In Panel D, we include old firms (ten years and older) and modify the regression from equation (7), interacting an indicator for young firms (age three and younger) with $LocalVintageCapital\_SIC3$:

$$
\begin{aligned}
\ln(1 + Investment_{1-3,i}) = & \beta_1 \ln(1 + LocalVintageCapital\_SIC3_{0,i}) + \\
& \beta_2 \ln(1 + LocalVintageCapital\_SIC3_{0,i}) \times YoungFirm_i + \quad (9) \\
& \beta_3 YoungFirm_i + \delta_{FE} + \varepsilon_i.
\end{aligned}
$$

Including old firms as a control allows us to include even finer fixed effects at the county-industry-year level that would not be possible in Panels A through C. These fixed effects account for any local industry trends and absorb the main effect on $\ln(1 + LocalVintageCapital\_SIC3)$ but still allow us to capture the interaction of interest. Effectively, our estimates compare

two firms in the same county-industry that make an investment at the same time, one of which is an old firm while the other is young. In columns (1) and (2), we find that young firms' subsequent investment, in terms of both quantities and breadth of investment, is significantly more sensitive to local vintage capital than that of old firms. Column (3) shows an economically smaller difference between young and old firms in the impact of old capital supply on subsequent investment in brand new machines. In conjunction with Panel A, the results indicate that local capital supply facilitates future investment in new equipment for young and old firms alike. One potential reason for this is that a healthy used capital market, possibly aided by growing young firms, allows older firms to refresh their capital stock more frequently, an implication that we investigate further in the Section 4.7.

4.6. Old Capital and New Firm (Job) Creation

Tables 7 and 8 indicate that local supply of old capital facilitates survival and growth of young firms, conditional on entry. We now ask whether local capital supply is important in creating start-ups in the first place. To answer this question, we turn to the LEHD data set, in which we observe employment in a county-industry (two-digit NAICS) among firms in different age categories. The outcome of interest is employment in firms aged zero to one year ($StartupEmployment$). The independent variable is an industry-level measure of local vintage capital as in Tables 7 and 8, except that the industry is measured as two-digit NAICS to conform to the LEHD data. The independent variable is lagged so that the regressions ask: does local vintage capital at a point in time facilitate startup entry and hiring over the next two years? The unit of observation is the county-industry-year. Specifically, in column (1) we estimate

$$\ln(1+StartupEmployment_{2,c,i,t}) = \beta \ln(1+LocalVintageCapital\_NAICS2_{0,c,i,t})+\delta_{FE}+\varepsilon_{c,i,t},$$
(10)

where c indexes counties, i industries (two-digit NAICS), t years, and numerical indices indicate the timing of measurement. Standard errors are clustered at the county and industry (two-digit NAICS) level.

We report the results in Table 9. The coefficient in column (1) suggests that a one-

33

standard-deviation increase in (log) local used capital results in about 63 percent more employment in start-ups two years later, which amounts to about 79 additional start-up employees relative to the mean of 126 per county-industry-year (standard deviation of 503). In column (2), we partition $LocalVintageCapital\_NAICS2$ into components based on equipment weight-to-value, as in Panel B of Table 8. The results suggest that less mobile equipment has a significantly stronger impact on new firm job creation. An F-test rejects equivalent effects of heavy and light equipment with a p-value of 0.048. In column (3), we partition $LocalVintageCapital\_NAICS2$ into components based on equipment market longevity. The results indicate that the effect of old capital on new firm job creation only exists among capital that is more likely to trade when old, with an F-test p-value of 0.020. In Appendix Table A10, we again interact the two measures to show that machine weight-to-value and market longevity act independently to mediate the influence of vintage capital availability on new firm job creation.

[**Insert Table 9 About Here.**]

As young firms are a significant driver of employment growth (Adelino et al., 2017), the results in Table 9 shed important light on the role of local vintage capital in job creation. Moreover, they provide relevant context to help interpret the young firm investment results from Tables 7 and 8. Since abundant used capital leads to additional start-up entry, we might expect that the bar has been lowered on firm quality. But the fact that young firms grow and succeed more in the presence of local used capital (as evidenced by additional depth and breadth of investment) suggests that the impact of vintage capital on firm dynamics is sufficient to offset any selection effect that lowers average firm quality. Furthermore, the results suggest that local vintage capital does not increase capital investment in young firms at the expense of new hiring. Instead, capital and labor serve as complements, with investment in each increasing when used local capital is abundant. Combined with the results from Table 3, these tables suggest that used capital is an important force in moderating and channeling the effects of financial constraints on start-up activity.

4.7. Young Firms and Incumbents' Investment Decisions

If young firms benefit from the availability of used local capital, a corollary prediction concerns the suppliers of that capital. In particular, how does the opportunity to sell old capital to start-ups impact the behavior of incumbents? One natural hypothesis is that the existence of an active entrepreneurial sector will increase the base of potential buyers for used equipment, thereby increasing machine turnover by incumbents.

Our final table measures the frequency of machine replacement, captured by the joint observation of a firm selling a previously acquired machine (which we observe as another firm purchasing it) and purchasing the same machine type. We then examine the probability of capital replacement for a given machine conditional on a measure of the relative employment share of young firms in the local economy that are natural users of the same equipment type. Specifically, we estimate

$$Replace_{0-T,i} = \beta YoungFirmShare_{0,i} + \delta_{FE} + \varepsilon_i. \tag{11}$$

The unit of observation is a piece of physical equipment acquired by an incumbent, defined as firms more than three years old.[22] Limiting observations to machines purchased by incumbents ensures we are not capturing the same firms in the left- and right-hand sides. $Replace_{0-T}$ is a dummy equal to one if the firm replaced the given piece of equipment within T years, where we examine three-, four-, and five-year replacement horizons.

The key independent variable, $YoungFirmShare$, is designed to capture variation in young firm demand across equipment types by measuring the employment share of local young firms (aged zero to three years) among industries that are potential buyers of a given equipment type. The variable is calculated for each machine type in each county-year as follows:

$$YoungFirmShare_{m,c,t} = \sum_{i \in I} IndustryWeight_{m,i} \times \frac{YoungFirmEmployment_{c,i,t}}{TotalEmployment_{c,i,t}}, \tag{12}$$

---

[22]We again drop any observations missing a company name and any non-end-user or government-entity buyers.

where m indexes machine types, c counties, t years, and i industries. $IndustryWeight_{m,i}$ captures the proportion of all machines of type m that were purchased by firms in industry i over the entire sample, where industry is defined at the two-digit NAICS level to conform to the employment data from LEHD QWI. For example, 60 percent of excavators may be purchased by construction firms and 40 percent by logging firms. For each equipment type, we then take a weighted average across industries of the share of employment in young firms in each county-industry-year (from LEHD QWI data). So if young firms account for 50 percent of construction employment and 25 percent of logging employment in Durham, NC in 2010, we would measure $YoungFirmShare$ in the Durham, NC excavator market in 2010 as $0.6 \times 0.5 + 0.4 \times 0.25 = 0.4$—the average of young firm employment share by industry, weighted by the importance of each industry for that equipment type.

One advantage of this measure is that it varies even within firm (and certainly within an industry-county) at a given point in time. For example, a Durham logger will benefit from young firm demand for his excavators via local construction employment—demand he might not enjoy for a log loader which can only be used by logging firms. Among incumbent logging firms, we would predict that log loaders would be replaced more slowly than excavators since they enjoy less young firm demand. Our measure allows us to identify the effects of young firm employment even with county-industry-time fixed effects, taking out local industry trends in investment and turnover. This within county-industry-time variation is central to the identification for the final table.

[Insert Table 10 About Here.]

Table 10 reports our findings. All regressions include fixed effects at the level of county-industry-year (of the original purchase) and machine type, with standard errors clustered by machine type. Columns (1) through (3) sequentially measure the impact on the probability of replacing a machine in three, four, and five years. To deal with truncation, we require three, four, and five years of remaining data for a given machine type to measure replacement within three, four and five years, respectively. We find that firms are more likely to replace equipment quickly when there are more young firms around. The effect begins to attenuate for five-year replacement horizons, though it is worth noting that this is longer than the

median (mean) equipment holding period of 3.2 (3.8) years.

The magnitudes appear plausible given estimation constraints. Note that the average probability of replacement at years three, four and five are just 0.01, 0.014, and 0.017—these numbers are likely biased down because of imperfect matching of machine serial numbers or because machines sold outside of the UCC database will be missed. However, given these mean frequencies, the effects of young firms on turnover are large. Moving $YoungFirmShare$ from zero to 100 percent among users of a given machine type increases the probability of three, four, and five year replacement by 0.017, 0.017, 0.009, more than doubling the probability of faster-than-average machine replacement.

5. Conclusion

We document a robust and ubiquitous pattern of capital acquisition and reallocation based on young (old) firms' appetite for old (new) capital. These complementary preferences based on capital age across the firm age spectrum appear to matter for local economies. On one hand, we find that start-up formation, as well as both the intensive and extensive margin of investment for new firms, depends on their co-location with used capital supply provided by older firms. At the same time, older firms appear to benefit from being near young buyers for their older capital.

Many interesting aspects of these patterns remain unexplored. For example, it is unclear how industry structure impacts the incentives of incumbents to seed their own future competition with cheap used capital supply. Meanwhile, if we take at face value the role for financing constraints in spurring demand for vintage capital, this would imply an important role for financial constraints in shaping competition and firm dynamism across industries and geographies based on trade in used capital.

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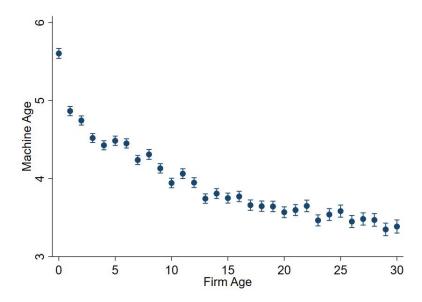
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Figure 1. Sample UCC Filings

UCC FINANCING STATEMENT
FOLLOW INSTRUCTIONS

A. NAME & PHONE OF CONTACT AT FILER (optional)
Corporation Service Company

B. E-MAIL CONTACT AT FILER (optional)
FilingDept@cscinfo.com

C. SEND ACKNOWLEDGMENT TO: (Name and Address)

Corporation Service Company
801 Adlai Stevenson Dr
Springfield, IL 62703

THE ABOVE SPACE IS FOR FILING OFFICE USE ONLY

1. DEBTOR'S NAME: Provide only one Debtor name (1a or 1b) (use exact, full name; do not omit, modify, or abbreviate any part of the Debtor's name); if any part of the Individual Debtor's name will not fit in line 1b, leave all of item 1 blank, check here ☐ and provide the Individual Debtor information in item 10 of the Financing Statement Addendum (Form UCC1Ad)

OR

1a. ORGANIZATION'S NAME			
HOSS TREE WORKS & LOGGING, LLC			
1b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)	SUFFIX
1c. MAILING ADDRESS	CITY	STATE / POSTAL CODE	COUNTRY
2917 REDWOOD RD	**DURHAM**	**NC** / **27704**	**USA**

2. DEBTOR'S NAME: Provide only one Debtor name (2a or 2b) (use exact, full name; do not omit, modify, or abbreviate any part of the Debtor's name); if any part of the Individual Debtor's name will not fit in line 2b, leave all of item 2 blank, check here ☐ and provide the Individual Debtor information in item 10 of the Financing Statement Addendum (Form UCC1Ad)

OR

2a. ORGANIZATION'S NAME			
2b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)	SUFFIX
2c. MAILING ADDRESS	CITY	STATE / POSTAL CODE	COUNTRY

3. SECURED PARTY'S NAME (or NAME of ASSIGNEE of ASSIGNOR SECURED PARTY): Provide only one Secured Party name (3a or 3b)

OR

3a. ORGANIZATION'S NAME			
De Lage Landen Financial Services, Inc.			
3b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)	SUFFIX
3c. MAILING ADDRESS	CITY	STATE / POSTAL CODE	COUNTRY
1111 Old Eagle School Road	**Wayne**	**PA** / **19087**	**USA**

4. COLLATERAL: This financing statement covers the following collateral:

```
1 (ONE) VERMEER SC40TX STUMP CUTTER S/N: 1VR0100J9J1000385, together with all components,
additions, upgrades, attachments, accessions, substitutions, replacements and proceeds of the
foregoing.  This filing relates only to the aforementioned collateral, and is not intended to
create or perfect a lien on all of the debtor's assets.
```

5. Check only if applicable and check only one box: Collateral is ☐ held in a Trust (see UCC1Ad, item 17 and Instructions) ☐ being administered by a Decedent's Personal Representative

6a. Check only if applicable and check only one box: ☐ Public-Finance Transaction ☐ Manufactured-Home Transaction ☐ A Debtor is a Transmitting Utility
6b. Check only if applicable and check only one box: ☐ Agricultural Lien ☐ Non-UCC Filing

7. ALTERNATIVE DESIGNATION (if applicable): ☐ Lessee/Lessor ☐ Consignee/Consignor ☐ Seller/Buyer ☐ Bailee/Bailor ☐ Licensee/Licensor

8. OPTIONAL FILER REFERENCE DATA:
[153214210]

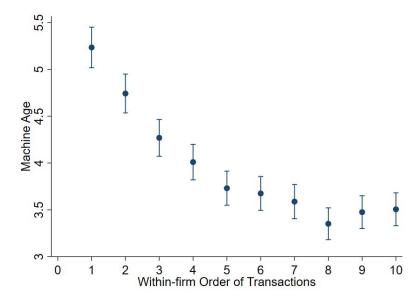FILING OFFICE COPY — UCC FINANCING STATEMENT (Form UCC1) (Rev. 04/20/11)

Notes. An example UCC filing from North Carolina for a Vermeer SC40TX stump cutter acquired by Hoss Tree Works and Logging in 2018.
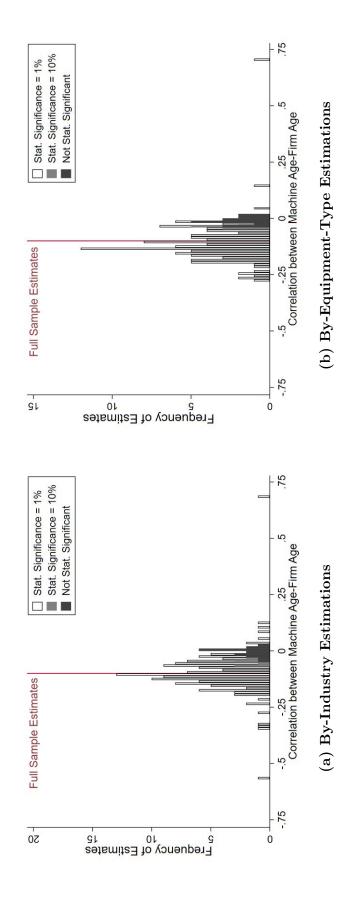
Figure 2. Firm Age and Machine Age

Notes. This graph plots the average age of machines purchased by firms across different age groups (0 to 30 years old), as well as the 95% confidence interval.

Figure 3. Trading Order and Machine Age

Notes. This graph plots the average age of machines purchased by firms across their own life cycles and the 95% confidence interval. The plot includes all (3,311) firms which i) were young (three-years old or younger) at the time of their first machine purchase and ii) had a machine purchase in at least ten different years. The x-axis measures the n-th year the firm purchased equipment, and the y-axis captures the average age of machines purchased in that n-th year.

Figure 4. Firm Age and Machine Age Estimation Coefficients: By-Industry and By-Equipment
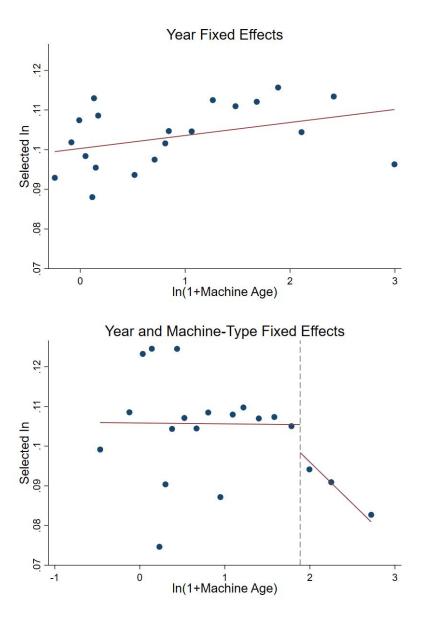

(a) **By-Industry Estimations**

(b) **By-Equipment-Type Estimations**

Notes. This graph plots the histogram of the industry-by-industry (Panel (a)) and equipment type-by-equipment type (Panel (b)) β correlations between firm age and machine age, estimated using

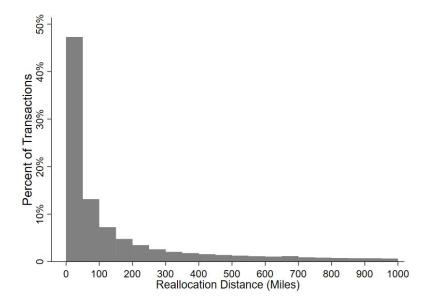$$\ln(1 + MachineAge_i) = \beta \ln(1 + FirmAge_i) + \epsilon_i.$$

We include each three-digit SIC industry for which we have at least 1,000 purchase observations in Panel (a) and each equipment type for which we have at least 1,000 purchase observations in Panel (b). The coefficients that are statistically significant at the 1% level are reported in white, those that are statistically significant only at the 10% level are reported in light gray, and those that are insignificant at the 10% level are reported in dark gray. Standard errors are robust to heteroskedasticity.

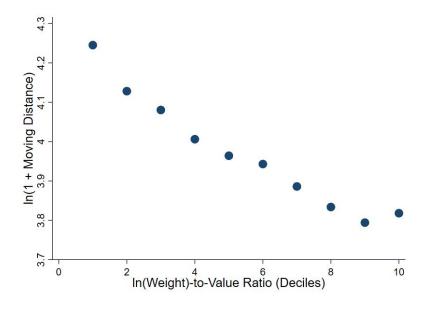**Figure 5. Sample Selection and Machine Age**

Notes. This figure depicts the relationship between sample inclusion/exclusion and machine age. The sample consists of the set of machines for which we observe a wholesale transaction at an equipment dealer. The y-axis, *Selected In*, is a dummy set equal to one if the machine reappeared as a retail sale within one year of being reported as part of an equipment dealer's wholesale floor-plan financing. The top figure shows a binned scatter plot of *Selected In* on the natural log of (1+) machine age, controlling for year fixed effects. The bottom figure adds machine-type fixed effects.

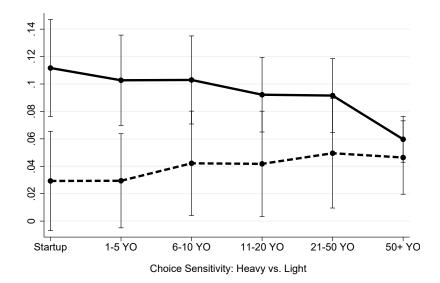**Figure 6. Histogram of Reallocation Distance**

Notes. This figure presents the histogram of reallocation distances (in miles) for equipment transactions. The distances are calculated based on the addresses provided in the UCC filings.
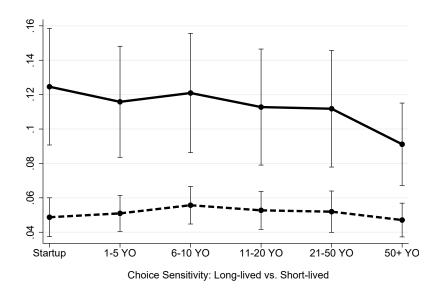
Figure 7. Weight-to-Value Ratio and Average Reallocation Distance

Notes. This figure presents a binned scattered plot of reallocation distance versus the ln(weight)-to-value ratio, conditional on the fixed effects from Panel B of Table 5. The weight-to-value measure varies at the equipment-type level and is calculated as the natural logarithm of the median equipment weight (in pounds) divided by the median price (in USD) when the equipment is sold new.

Figure 8. Effect of Local Vintage Capital Supply on Equipment Choice—By Firm Age, Machine WTV, and Longevity

Choice Sensitivity: Heavy vs. Light

Choice Sensitivity: Long-lived vs. Short-lived

Notes. This figure plots the average response of equipment purchase choices to local vintage capital supply across different firm age groups and machine-type characteristics (*Heavy* versus *Light* and *Long-lived* versus *Short-lived*) defined in Section 4.3. The reported coefficients are estimated from the following model

$$ChosenMachine = \beta \times LocalVintageCapital\_MT + \delta_{FE} + \varepsilon,$$

using the fixed effects from column (1) of Table 6. We collect firms into six age groups that are reported on the horizontal axis. 95% confidence intervals are reported for each estimated point, with standard errors double clustered at the industry (three-digit SIC) and county level. *Heavy* (*Light*) and *Long-lived* (*Short-lived*) coefficients are represented by the solid (dashed) lines.

Table 1
Summary Statistics

Panel A: Firm and Machine Characteristics.

	Mean	Std.Dev	p25	Median	p75
Firm age (years)	22.2	24.1	6	16	29
Machine age (years)	3.8	6.5	0	1	5
Equipment value ($USD)	80,677	98,710	24,824	51,402	102,149

Panel B: Machine Transactions Tabulated by Buyer Industry.

				Percentage	
NAICS	Sector	Observations	UCC	2019 GDP	Diff.
11	Agriculture, forestry, fishing and hunting	133,834	8.60	0.93	7.67
21	Mining, quarrying, and oil and gas extraction	28,788	1.85	1.65	0.20
22	Utilities	5,762	0.37	1.78	-1.41
23	Construction	591,752	38.03	4.75	33.28
31-33	Manufacturing	212,507	13.66	12.48	1.18
42	Wholesale trade	96,249	6.19	6.72	-0.53
44-45	Retail trade	46,637	3.00	6.18	-3.18
48-49	Transportation and warehousing	69,188	4.45	3.71	0.74
51	Information	5,516	0.35	6.00	-5.65
52	Finance and insurance	12,915	0.83	8.86	-8.03
53	Real estate and rental and leasing	21,395	1.37	15.30	-13.93
54	Professional, scientific, and technical services	63,365	4.07	8.72	-4.65
55	Management of companies and enterprises	2,118	0.14	2.19	-2.05
56	Administrative and support and waste management and remediation services	120,733	7.76	3.52	4.24
61	Educational services	45,217	2.91	1.44	1.47
62	Health care and social assistance	46,407	2.98	8.49	-5.51
71	Arts, entertainment, and recreation	5,158	0.33	1.27	-0.94
72	Accommodation and food services	4,661	0.30	3.56	-3.26
81	Other services (except public administration)	34,282	2.20	2.45	-0.25
92	Public administration	1,904	0.12	0.00	0.12
99	Industries not classified	7,750	0.50	0.00	0.50
Total		1,556,138	100	100	

Notes. Panel A provides descriptive statistics on the main sample of equipment purchases. Firm age is the difference between the year of equipment purchase and the firm founding year, as reported by EDA (sourced from Dun & Bradstreet). Machine age is the difference between the year of equipment purchase and the year of machine production. Equipment value is estimated by EDA based on the equipment model and age. Panel B provides the industry distribution of the equipment purchases in the main sample of machine purchases. The table reports transactions based on buyer industries across the two-digit NAICS sectors. The 2019 distribution of GDP across these sectors from the BEA is shown for reference, along with the difference between the UCC share and the GDP share.

Table 2

Firm Age and Machine Age in Equipment Transactions

	(1)	(2)	(3)	(4)
		ln(1+Machine Age)		
ln(1+Firm Age)	-0.088***	-0.097***	-0.085***	-0.088***
	[0.008]	[0.008]	[0.028]	[0.008]
Observations	1,556,138	1,556,138	1,556,138	1,556,138
R^2	0.240	0.352	0.533	0.583
County-Year FE	Y	Y		
Industry (SIC-3) FE	Y	Y		
Machine Type FE		Y		
Firm FE			Y	
Machine FE				Y

Notes. This table documents the relationship between buyer firm age and machine age in equipment transactions. *Machine Age* is the difference between the original manufacture year and the year of the transaction. *Firm Age* is the difference between the firm founding year and the year of the transaction. We add one to both age variables before taking the natural log. Fixed effects included in the various models are reported. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3

Firm Age and Machine Age—Credit Conditions and Model Age

	(1)	(2)	(3)	(4)	(5)	(6)
		ln(1+Machine Age)			ln(1+Model Age)	
ln(1+Firm Age)	-0.101***	-0.112***	-0.091***	-0.100***	-0.003	-0.003*
	[0.010]	[0.007]	[0.008]	[0.008]	[0.004]	[0.002]
ln(1+Firm Age) x Shale Shock	0.020***	0.024***				
	[0.007]	[0.008]				
ln(1+Firm Age) x Lease			0.059***	0.073***		
			[0.010]	[0.006]		
Observations	734,295	734,295	2,540,674	2,540,674	880,346	880,346
R^2	0.225	0.344	0.241	0.339	0.243	0.334
County-Year FE	Y	Y	Y	Y	Y	Y
Industry (SIC-3) FE	Y	Y	Y	Y	Y	Y
Machine Type FE	Y	Y	Y	Y		
Leasing FE			Y	Y		

Notes. Columns (1) through (4) examine how the relationship between machine age and buyer firm age depends on financial constraints. The model setup follows that in Table 2. *Machine Age* is the difference between the original manufacture year and the year of the transaction. *Firm Age* is the difference between the firm founding year and the year of the transaction. In columns (1) and (2), we interact *ln(1+Firm Age)* with a dummy variable, *Shale Shock*, indicating above-median availability of credit transmitted from distant shale oil shocks through the bank branch network to local branches, following the definition of Gilje, Loutskina, and Strahan (2016). The sample size drops in this set of regressions because the shale oil shock is only available from 2002–2011. In columns (3) and (4), we add lease transactions to the main sample of machine purchases. We interact *ln(1+Firm Age)* with a dummy variable, *Lease*, indicating lease transactions. Columns (5) and (6) examine the relationship between model (technological) age and buyer firm age. *Model Age* is calculated as the number of years between the transaction date and the introduction of the specific make and model. The analysis is performed only on the transactions involving new machines. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

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Table 4

Firm Age and Machine Age excluding Old Machines

	(1)	(2)	(3)	(4)
		ln(1+Machine Age)		
	Full Sample (Table 2)		Machine Age ≤ 10 Only	
ln(1+Firm Age)	-0.088***	-0.097***	-0.073***	-0.079***
	[0.008]	[0.008]	[0.009]	[0.010]
Observations	1,556,138	1,556,138	1,382,608	1,382,608
R^2	0.240	0.352	-	-
Model	OLS		Truncated Regression	
County-Year FE	Y	Y	Y	Y
Industry (SIC-3) FE	Y	Y	Y	Y
Machine Type FE		Y		Y

Notes. This table compares the full sample relationship between machine age and firm age (columns (1) and (2), repeated from Table 2) with the same relationship for the subset of machines aged ten years or less (columns (3) and (4)). *Machine Age* is the difference between the original manufacture year and the year of the transaction. *Firm Age* is the difference between the firm founding year and the year of the transaction. Columns (3) and (4) are estimated using truncated regressions to account for the bias induced by truncated dependent variables. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Geographical Patterns of Equipment Reallocation

Panel A: Machine Age.

	(1)	(2)	(3)	(4)
	ln(1+Moving Distance)		I(Same County)	
ln(1+Machine Age)	-0.133***		0.026***	
	[0.012]		[0.003]	
n^{th} Reallocation		-0.085***		0.016***
		[0.014]		[0.002]
Observations	382,360	382,360	382,360	382,360
R^2	0.134	0.133	0.096	0.095
Year FE	Y	Y	Y	Y
Industry (SIC-3) FE	Y	Y	Y	Y
Machine Type FE	Y	Y	Y	Y
Buyer County FE	Y	Y	Y	Y
Seller County FE	Y	Y	Y	Y

Panel B: Machine Weight-to-Value.

	(1)	(2)
	ln(1+Moving Distance)	I(Same County)
ln(Weight)/Value (deciles)	-0.098***	0.014***
	[0.018]	[0.002]
Observations	382,360	382,360
R^2	0.121	0.089
Year FE	Y	Y
Industry (SIC-3) FE	Y	Y
Buyer County FE	Y	Y
Seller County FE	Y	Y

Notes. This table documents the relationship between the reallocation distance of a machine in a transaction and machine age (Panel A) or machine weight-to-value (Panel B). The sample contains all machines for which we observe machine age and more than one purchase. *Moving Distance* is the distance (in miles) between the buyer and the seller of a machine, and *I(Same County)* is a dummy variable indicating whether the transaction was between two parties in the same county. *Machine Age* is the number of years between the original manufacture date and the date of the transaction. As an alternative measure to capture machine age, n^{th} *Reallocation* is one for the first reallocation we observe on a particular machine, two for the second, and so on. We drop reallocations to the fifth owner or later (0.2 percent of observations) to mitigate outlier influence. In Panel B, the dependent variable is deciles of *ln(Weight)/Value*, which varies at the machine-type level as described in Section 4.3. In Panel A, we control for fixed effects at the level of year, industry (three-digit SIC), machine type, buyer county, and seller county. We omit machine-type fixed effects in Panel B because they would subsume the dependent variable. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6

Equipment Purchase Choice and Local Vintage Capital Supply

	(1)	(2)	(3)	(4)	(5)
	Heavy × Long-lived		Chosen Machine = 1 ~(Heavy × Long-lived)	Young Firms	
ln(1+Local Vintage Capital MT) (std.)	0.129*** [0.021]	0.142*** [0.025]	0.070*** [0.010]	0.035*** [0.018]	0.051*** [0.005]
ln(1+Local Vintage Capital MT) (std.) × ln(1+Firm Age)		-0.004*** [0.002]	0.000 [0.000]		
ln(1+ Firm Age)		0.000 [0.002]	0.000 [0.000]		
ln(1+Local Vintage Capital MT) (std.) × Heavy				0.056*** [0.019]	
ln(1+Local Vintage Capital MT) (std.) × Long-lived					0.068*** [0.013]
Observations	320,601	320,601	4,279,743	361,303	755,871
R^2	0.505	0.505	0.445	0.485	0.436
County-Year-Equipment Category FE	Y	Y	Y	Y	Y
Machine Type FE	Y	Y	Y	Y	Y

Notes. This table examines the equipment purchase choice of firms in response to local vintage capital supply. For each realized transaction, we construct a set of "pseudo transactions" by pairing the buyer with all the other possible equipment types under the same equipment category. The unit of observation is a potential machine purchase, and the dependent variable (*Chosen Machine*) is equal to one for the actual machine purchased and zero for the pseudo transactions. Columns (1) and (2) include only machines that are categorized as both *Heavy* and *Long-lived*, as defined in Section 4.3. Column (3) includes the complementary set of all machines that are not categorized as both *Heavy* and *Long-lived.* Columns (4) and (5) include only observations in which the purchasing firm is young (three years old or less). Column (4) includes only *Heavy* and *Light* equipment so that the interaction compares heavy to light equipment. *Local Vintage Capital MT* varies at the machine type-county-year level and is defined in Section 4.1 based on local transaction histories. (std.) denotes that the variable is standardized to have a mean of zero and standard deviation of one for interpretation. *Firm Age* is the difference between the firm founding year and the year of the transaction. Standard errors are double clustered at the industry (three-digit SIC) and county level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The difference between coefficients on ln(1+*LocalVintageCapitalMT*) × ln(1+*FirmAge*) in columns (2) and (3) is -0.005 and is significant at the 1% level.

Table 7
Local Vintage Capital and Start-up Investment

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Machines		ln(1+Investment(1,3)) Machine Types		New Machines	
ln(1+Local Vintage Capital SIC-3) (std.)	0.082***	0.076***	0.067***	0.062***	0.053***	0.045***
	[0.014]	[0.016]	[0.011]	[0.012]	[0.009]	[0.009]
Observations	71,722	71,722	71,722	71,722	71,722	71,722
R^2	0.102	0.231	0.108	0.238	0.077	0.203
County FE	Y		Y		Y	
Industry (SIC-3) FE	Y		Y		Y	
Year FE	Y		Y		Y	
County-Year FE		Y		Y		Y
Industry (SIC-3)-Year FE		Y		Y		Y

Notes. This table examines the relationship between start-up investment activity and local vintage capital availability. The sample includes all firms for which we observe a machine acquisition in their first three years. The outcome variables capture the natural log of (1+) investment during the period one to three years after the firm's first machine acquisition. *Total Machines* measures investment as the total number of equipment acquisitions. *Machine Types* captures the number of different equipment types acquired. *New Machines* captures the total number of acquisitions of brand new equipment. *Local Vintage Capital SIC-3*, measured at the time of the firm's first machine acquisition, varies at the industry-county-year level and is defined in Section 4.1 based on local transaction histories. (std.) denotes that the variable is standardized to have a mean of zero and standard deviation of one for interpretation. Standard errors are double clustered at industry (three-digit SIC) and county level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Local Vintage Capital and Start-up Investment: Heterogeneity

Panel A: Local Vintage Capital and Young Firm Growth (reproduced from Table 7)

	(1)	(2)	(3)
		ln(1+Investment(1,3))	
	Total Machines	Machine Types	New Machines
ln(1+Local Vintage Capital SIC-3) (std.)	0.076***	0.062***	0.045***
	[0.016]	[0.012]	[0.009]
Observations	71,722	71,722	71,722
R^2	0.231	0.238	0.203
County-Year FE	Y	Y	Y
Industry (SIC-3)-Year FE	Y	Y	Y

Panel B: Heavy vs. Light Machines

	(1)	(2)	(3)
		ln(1+Investment(1,3))	
	Total Machines	Machine Types	New Machines
ln(1+LVC Heavy) (norm.)	0.160***	0.118***	0.110***
	[0.053]	[0.042]	[0.037]
ln(1+LVC Mid-weight) (norm.)	0.117***	0.097***	0.070***
	[0.036]	[0.029]	[0.022]
ln(1+LVC Light) (norm.)	0.032	0.027	0.015
	[0.023]	[0.020]	[0.016]
Observations	71,722	71,722	71,722
R^2	0.231	0.238	0.203
County-Year FE	Y	Y	Y
Industry (SIC-3)-Year FE	Y	Y	Y
p-value of *Heavy* vs. *Light*	0.040	0.067	0.023

Notes. This table examines the relationship between start-up investment activity and local vintage capital availability. The outcome variables capture the natural log of (1+) investment during the period one to three years after the firm's first machine acquisition, measured three ways. *Total Machines* measures investment as the total number of equipment acquisitions. *Machine Types* captures the number of different equipment types acquired. *New Machines* captures the total number of acquisitions of brand new equipment. *Local Vintage Capital SIC-3* (Panels A and D), measured at the time of the firm's first machine acquisition, varies at the industry-county-year level and is defined in Section 4.1 based on local transaction histories. (std.) denotes that the variable is standardized to have a mean of zero and standard deviation of one for interpretation. In

Panel C: Long-Lived vs. Short-Lived Machines

	(1)	(2)	(3)
		ln(1+Investment(1,3))	
	Total Machines	Machine Types	New Machines
ln(1+LVC Long-lived) (norm.)	0.093***	0.075***	0.054***
	[0.019]	[0.015]	[0.010]
ln(1+LVC Short-lived) (norm.)	-0.083	-0.069	-0.038
	[0.080]	[0.064]	[0.056]
Observations	71,722	71,722	71,722
R^2	0.231	0.238	0.203
County-Year FE	Y	Y	Y
Industry (SIC-3)-Year FE	Y	Y	Y
p-value of *Long* vs. *Short*	0.052	0.047	0.118

Panel D: Young vs. Old Firms

	(1)	(2)	(3)
		ln(1+Investment(1,3))	
	Total Machines	Machine Types	New Machines
ln(1+Local Vintage Capital SIC-3) (std.)	0.018***	0.017***	0.007*
$\times$ Young Firm	[0.005]	[0.005]	[0.004]
Young Firm	0.017**	0.016**	0.001
	[0.007]	[0.007]	[0.005]
Observations	385,458	385,458	385,458
R^2	0.387	0.389	0.373
County-Industry (SIC-3)-Year FE	Y	Y	Y

Notes (cont.). Panel B, *Local Vintage Capital SIC-3* is partitioned into three components. *LVC Heavy* is the component consisting of heavy (high log(weight)-to-value) equipment, as defined in Section 4.3, and similarly for *LVC Mid-weight* and *LVC Light*. (norm.) denotes that the components have been normalized so that a one-unit change in each component corresponds to a one-standard-deviation change in *ln(1+Local Vintage Capital SIC-3)*, making all coefficients in Panels A through C directly comparable. (See Appendix Section A.2 for a detailed description). In Panel C, *Local Vintage Capital SIC-3* is partitioned into two components. *LVC Long-lived* is the component consisting of long-lived equipment, as defined in Section 4.3, and similarly for *LVC Short-lived*. Panels A through C include only investment by young firms (aged three years and younger) at the time of the initial investment. Panel D adds old firms (aged 10 years and older). *Young Firm* (Panel D) is an indicator for firms aged three years and younger. Standard errors are double clustered at the industry (three-digit SIC) and county level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9

Table 9

Local Vintage Capital and Start-up Employment

	(1)	(2)	(3)
	ln(1+Start-up Employment (t=2))		
ln(1+Local Vintage Capital NAICS-2) (std.)	0.628**		
	[0.264]		
ln(1+LVC NAICS-2 Heavy) (norm.)		2.931**	
		[1.356]	
ln(1+LVC NAICS-2 Mid-weight) (norm.)		0.536***	
		[0.153]	
ln(1+LVC NAICS-2 Light) (norm.)		0.404*	
		[0.231]	
ln(1+LVC NAICS-2 Long-lived) (norm.)			0.752**
			[0.272]
ln(1+LVC NAICS-2 Short-lived) (norm.)			0.104
			[0.253]
Observations	232,510	232,510	232,510
R^2	0.721	0.722	0.721
County-Year FE	Y	Y	Y
Industry (NAICS-2)-Year FE	Y	Y	Y
p-value of F-test		0.048	0.020

Notes. This table examines the relationship between start-up employment and local vintage capital availability. The unit of observation is a county-industry-year, where industry is two-digit NAICS. *Start-up Employment (t=2)* is the number of new jobs created by start-ups from $t = 0$ to $t = 2$ as reported in the Census LEHD QWI data. *Local Vintage Capital NAICS-2*, measured at $t = 0$, varies at the industry-county-year level and is defined in Section 4.1 based on local transaction histories. (std.) denotes that the variable is standardized to have a mean of zero and standard deviation of one for interpretation. In column (2), *Local Vintage Capital NAICS-2* is partitioned into three components. *LVC NAICS-2 Heavy* is the component consisting of heavy (high log(weight)-to-value) equipment, as defined in Section 4.3, and similarly for *LVC NAICS-2 Mid-weight* and *LVC NAICS-2 Light*. (norm.) denotes that the components have been normalized so that a one-unit change in each component corresponds to a one-standard-deviation change in *ln(1+Local Vintage Capital NAICS-2)*, making all coefficients in the table directly comparable. (See Appendix Section A.2 for a detailed description). In column (3), *Local Vintage Capital NAICS-2* is partitioned into two components. *LVC NAICS-2 Long-lived* is the component consisting of long-lived equipment, as defined in Section 4.3, and similarly for *LVC NAICS-2 Short-lived*. Standard errors are double clustered at the industry (two-digit NAICS) and county level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10
Incumbent Capital Replacement

	(1)	(2)	(3)
		Replace(0,T)	
	≤ 3 Years	≤ 4 Years	≤ 5 Years
Young Firm Share	0.017***	0.017***	0.009
	[0.005]	[0.006]	[0.008]
Observations	845,812	772,248	692,232
R^2	0.164	0.174	0.180
County-Industry (NAICS-2)-Year FE	Y	Y	Y
Machine Type FE	Y	Y	Y

Notes. This table documents the relationship between the replacement period for a machine purchased by an incumbent firm and the resale market demand for that machine type coming from local young firms. Incumbent firms are those greater than three years old, and young firms are three years old or younger. The sample consists of all machine purchases by incumbent firms at least three, four, or five years before the end of the sample (for columns (1), (2), and (3), respectively). *Replace(0,T)* is an indicator equal to one if the incumbent firm sold a given machine (based on a subsequent purchase with the same serial number but matched to a different firm) and purchased an identical machine type within T years after acquiring it. Columns (1), (2), and (3) correspond to $T = 3, 4$, and 5, respectivley. *Young Firm Share* is the average (across industries in a given county) of employees working in 0–3 year-old firms scaled by total employees in the county-industry pair. The average is weighted based on the percentage of machines of the same type purchased by each industry over the entire sample (see equation 12 in the text; an example calculation is also provided in Section 4.7). Industry classification in this table is at the two-digit NAICS level to correspond to the LEHD QWI data used to calculate *Young Firm Share*. 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.

Online Appendix (Not For Publication)

A. Additional Details on Data and Measurements

A.1. Constructing Shale Shocks

We utilize a county-year 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 2002 to 2011 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 *ex-ante* fraction of total deposits held in a windfall county. This generates a bank-year level variable which we average at the county-year in non-windfall counties using the weight of those banks in the county. Formally, the variable *ShaleLiquidity* is defined as

$$ShaleLiquidity_{c,t} = \sum_{b \in B(c)} BankWeight_{b,c,2002} \times \sum_{c \in C} BankWeight_{b,c,2002} \times BankShare_{b,c,2002} \times W_{c,t}.$$

(A1)

$W_{c,t}$ is the number of oil wells that have been discovered in county c by year t; $BankShare_{b,c,2002}$ is the fraction of deposits that bank b held in county c as of 2002 as a fraction of total deposits in that county in 2002; and $BankWeight_{b,c,2002}$ is the fraction of deposits that bank b held in county c in 2002 as a fraction of total deposits in that bank in 2002. We then define *ShaleShock* as an indicator variable for above-median values of *ShaleLiquidity*. Ideally, the measure allows us to capture 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.

A.2. Scaling of Vintage Capital Components

In Table 7 we estimate the effect of local vintage capital availability on young firm growth as captured by subsequent investment activity:

$$\ln(1 + Investment_{1-3,i}) = \beta \ln(1 + LocalVintageCapital\_SIC3_{0,i}) + \delta_{FE} + \varepsilon_i. \quad (A2)$$

These regressions are designed to inform the following thought experiment: suppose that there is \$100 million of used logging equipment in Durham, NC in 2010. What would happen to the investment dynamics of young logging firms in Durham if we were to drop an additional one percent (in this case, \$1 million) of used logging equipment in the county?[23]

We then test for differential effects of vintage capital on young firm growth in Table 8 by partitioning $LocalVintageCapital\_SIC3$ into components based on equipment weight-to-value:

$$\ln(1 + Investment_{1-3,i}) = \beta_h \ln(1 + LVC\_Heavy_{0,i}) + \beta_m \ln(1 + LVC\_Midweight_{0,i}) +$$
$$\beta_l \ln(1 + LVC\_Light_{0,i}) + \delta_{FE} + \varepsilon_i.$$

$$(A3)$$

With these regressions, we want to ask whether it makes a difference to young firm investment dynamics if the additional \$1 million in logging equipment comes from heavy versus light equipment. The null hypothesis is that equation (A2) is the true model—that is, all equipment, regardless of weight-to-value, has the same impact on subsequent young firm investment. We test this null by comparing β_h to β_l. To facilitate this comparison, we scale each independent variable such that the interpretation of β_h (β_m, β_l) is the effect of a one-standard-deviation increase in (log) *total* equipment supply coming exclusively from additional *heavy* (*mid-weight, light*) equipment. Below we describe why this scaling is necessary and how we accomplish it.

To begin, imagine we ran the regressions in equation (A3) without any scaling. Then β_h would tell us the impact on young firm investment of a one percent change in LVC_Heavy,

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[23]In the paper, we standardize $\ln(1 + LocalVintageCapital\_SIC3_{0,i})$ to have a mean of zero and standard deviation of one for interpretation. We ignore this standardization for the moment but will return to it shortly.

which amounts to a 0.167 percent change in $LocalVintageCapital\_SIC3$ (since heavy capital accounts for 16.7 percent of total vintage capital). That is, under the null, $\beta_h = 0.167 \cdot \beta$.[24] Meanwhile, β_l would capture the impact of a 0.358 percent change in $LocalVintageCapital\_SIC3$, as light capital makes up 35.8 percent of total vintage capital (so $\beta_l = 0.358 \cdot \beta$ under the null). In the context of the thought experiment, we would be comparing the impact on young firm investment of an additional \$0.167 million of heavy logging equipment in Durham, NC to the impact of an additional \$0.358 million of light logging equipment, instead of \$1 million of each type as we set out to do.

To capture the effect of an additional \$1 million in heavy logging equipment, we need to gross up β_h by $\frac{1}{0.167}$, which we accomplish by multiplying $\ln(1 + LVC\_Heavy)$ by 0.167, the proportion of total equipment supply coming from heavy equipment (and similarly for mid-weight and light equipment). A unit change in $\ln(1 + LVC\_Heavy) \cdot 0.167$ corresponds to a $\frac{1}{0.167}$ percent change in LVC_Heavy, which in turn is equivalent to a one percent change in $LocalVintageCapital\_SIC3$. After this scaling, the interpretation of β_h (β_m, β_l) is the effect of a one percent increase in *total* equipment supply coming exclusively from additional *heavy* (*mid-weight, light*) equipment. With the amount of additional equipment set equal across weight-to-value categories, we can now ask whether heavy equipment is more impactful than light equipment by comparing β_h to β_l, which should be equal under the null.[25]

Throughout the paper we standardize $\ln(1 + LocalVintageCapital\_SIC3)$ in our regressions for ease of interpretation. For consistency, we also want to interpret β_h, β_m, and β_l as the effects of a one-standard-deviation change in (log) *total* vintage capital. This requires a second step in which we divide each right-hand-side variable in equation (A3) by the standard deviation of $\ln(1 + LocalVintageCapital\_SIC3)$. Thus, β_h (β_m, β_l) captures the impact of a

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[24]More formally, if we let y represent the log of investment,

$$
\begin{aligned}
\beta_h &= \frac{\partial y}{\partial \ln(LVC\_Heavy)} \\
&= \frac{\partial y}{\partial \ln(LocalVintageCapital\_SIC3)} \cdot \frac{\partial ln(LocalVintageCapital\_SIC3)}{\partial \ln(LVC\_Heavy)} \\
&= \beta \cdot \frac{LVC\_Heavy}{LocalVintageCapital\_SIC3},
\end{aligned}
$$

where the last equality follows from the fact that $LocalVintageCapital\_SIC3 = LVC\_Heavy + LVC\_Midweight + LVC\_Light$. The same is true for mid-weight or light equipment.
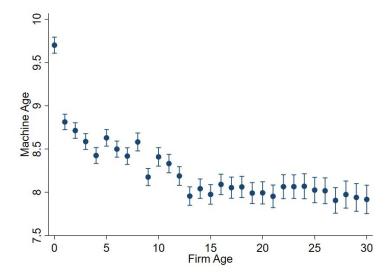
[25]In fact, given the particular scaling, $\beta = \beta_h = \beta_m = \beta_l$, which we confirm with simulations.

one-standard-deviation change in (log) *total* vintage capital coming from additional *heavy* (*mid-weight*, *light*) vintage capital. Whereas the first scaling is a matter of correctness for comparing β_h to β_l, this second step is simply a matter of consistency in interpretation. In particular, it has no effect on the t-stats for individual coefficients nor on the F-stats for comparing coefficients.

We apply the two-step scaling described above to $\ln(1+LVC\_Heavy)$, $\ln(1+LVC\_Midweight)$, and $\ln(1+LVC\_Light)$ in Panel B of Table 8 as well as in Table 9. We follow an analogous process to scale $\ln(1+LVC\_LongLived)$ and $\ln(1+LVC\_ShortLived)$ for Panel C of Table 8 and Table 9.
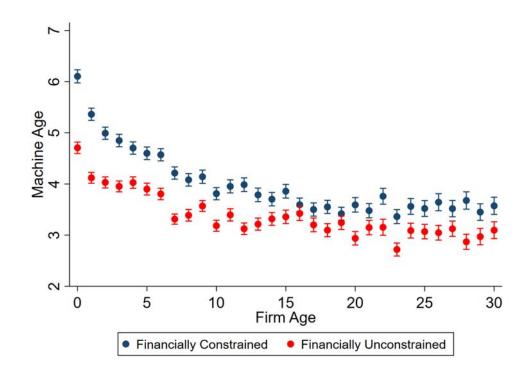
B. Additional Results

Figure A1. Firm Age and Machine Age—Used Capital Only

Notes. This graph plots the average age of machines purchased by firms across different age groups (0 to 30 years old), as well as the 95% confidence interval. The graph uses only transactions of used machines.

Figure A2. Firm Age and Machine Age Across Constrained vs. Unconstrained Conditions
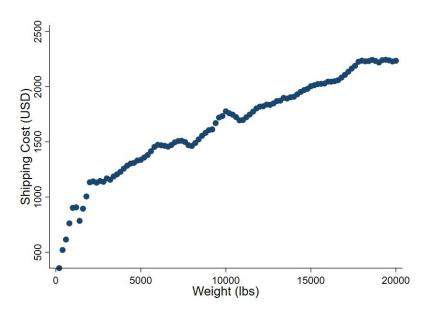

Notes. This graph plots the average age of machines purchased by firms across different age groups (0 to 30 years old), as well as the 95% confidence interval. We plot firms in financially constrained vs. unconstrained conditions separately, where the levels of financial constraint are defined by the *ShaleShock* indicator in the paper.

Figure A3. Relation between Equipment Weight and Shipping Cost

Notes. This figure plots the average shipping cost of equipment as a function of the machine weight. Shipping costs are sampled through freight shipping broker uShip (www.uship.com). For each equipment weight (in 200 pound increments from 200 to 20,000 pounds), we quote 40 different shipping routes, identical across weights, ranging from same-county to cross-country routes. We plot the average shipping cost across these 40 routes against the weight.

Table A1
Acquisition Frequency by Firm and Machine Age Decile

		Machine Age Decile			Total
		1	...	10	
Firm Age Decile	1	57,207		25,108	176,858
		9.2%		16.4%	
	...				
	10	82,218		7,224	150,710
		13.2%		4.7%	
	Total	625,203		153,599	

Notes. This table reports transaction frequencies by machine and firm age deciles for the highest and lowest deciles. Note, the first decile of machine age is over-represented as it contains all new machines.

Table A2
Main Results with Inverse Hyperbolic Sine Transformation

	(1)	(2)	(3)	(4)
		IHS(1+Machine Age)		
IHS(1+Firm Age)	-0.084***	-0.092***	-0.085***	-0.085***
	[0.008]	[0.008]	[0.028]	[0.007]
Observations	1,556,138	1,556,138	1,556,138	1,556,138
R^2	0.241	0.356	0.537	0.594
County-Year FE	Y	Y		
Industry (SIC-3) FE	Y	Y		
Machine Type FE		Y		
Firm FE			Y	
Machine FE				Y

Notes. This table reproduces Table 2 in the paper with firm age and machine age variables being transformed using inverse hyperbolic sine transformation instead of natural logarithm. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A3
Firm Age and Machine Age by Industry

| NAICS | Sector | Percentage | | | |
		UCC	2019 GDP	Diff.	β
81	Other services (except public administration)	2.20	2.45	-0.25	-0.197
42	Wholesale trade	6.19	6.72	-0.53	-0.190
56	Administrative and support and waste management and remediation services	7.76	3.52	4.24	-0.175
54	Professional, scientific, and technical services	4.07	8.72	-4.65	-0.160
44-45	Retail trade	3.00	6.18	-3.18	-0.151
31-33	Manufacturing	13.66	12.48	1.18	-0.146
11	Agriculture, forestry, fishing and hunting	8.60	0.93	7.67	-0.141
22	Utilities	0.37	1.78	-1.41	-0.138
51	Information	0.35	6.00	-5.65	-0.121
71	Arts, entertainment, and recreation	0.33	1.27	-0.94	-0.105
52	Finance and insurance	0.83	8.86	-8.03	-0.097
23	Construction	38.03	4.75	33.28	-0.096
53	Real estate and rental and leasing	1.37	15.30	-13.93	-0.093
21	Mining, quarrying, and oil and gas extraction	1.85	1.65	0.20	-0.088
99	Industries not classified	0.50	0.00	0.50	-0.077
55	Management of companies and enterprises	0.14	2.19	-2.05	-0.072
92	Public administration	0.12	0.00	0.12	-0.064
72	Accommodation and food services	0.30	3.56	-3.26	-0.044
61	Educational services	2.91	1.44	1.47	-0.030
48-49	Transportation and warehousing	4.45	4.45	0.74	-0.012
62	Health care and social assistance	2.98	8.49	-5.51	-0.011

Notes. This table provides the industry-by-industry β correlations between firm age and machine age, estimated using

$$\ln(1 + MachineAge_i) = \beta \ln(1 + FirmAge_i) + \epsilon_i.$$

for each two-digit NAICS industry. The industries are sorted from largest to smallest correlation (in absolute value). Each coefficient is significant at the 1% level with standard errors clustered at the machine type level. The proportion of the observations in each industry in the UCC data are reported next to the 2019 proportion of GDP in each industry from the BEA (and the difference between the two).

Table A4

Firm Age and Machine Age in Equipment Transactions: Re-weighted

	(1)	(2)	(3)	(4)
		ln(1+Machine Age)		
	UCC Weights (Table 2)		GDP Weights	
ln(1+Firm Age)	-0.088***	-0.097***	-0.080***	-0.073***
	[0.008]	[0.008]	[0.010]	[0.012]
Observations	1,556,138	1,556,138	1,546,484	1,546,484
R^2	0.240	0.352	0.363	0.453
County-Year FE	Y	Y	Y	Y
Industry (SIC-3) FE	Y	Y	Y	Y
Machine Type FE		Y		Y

Notes. This table examines the impact of sample selection in the UCC data on the estimated relationship between firm age and machine age. *Machine Age* is the difference between the original manufacture year and the year of the transaction. *Firm Age* is the difference between the firm founding year and the year of the transaction. We add one to both age variables before taking the natural log. Columns (1) and (2) are reproduced from the first two columns of Table 2. In columns (3) and (4), we re-weight the data so that the distribution of machine purchases across two-digit NAICS industries matches the distribution of GDP in the 2019 BEA data. The observation count drops in columns (3) and (4) because the BEA data do not cover NAICS sector 92 (Public administration) nor 99 (Industries not classified), which together account for 0.6 percent of the UCC sample. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A5
Firm Age Distribution in UCC and Census LEHD QWI

Firm Age	Census Employment (%)	UCC Equipment Purchase (%)
0-1 YO	7.61	7.73
2-3 YO	7.32	7.21
4-5 YO	6.73	6.80
6+ YO	78.34	78.26

Notes. This table compares the firm age distribution as captured by transactions in the UCC sample and employment in the Census LEHD QWI sample. For the LEHD data, we compute the average across county-industry-quarters of the employment share in each age category. The Census Bureau deliberately injects noise (including some missing values) to prevent the ability to back out firm identities. To constrain the LEHD percentages to add to 100, the percentage reported for the 6+ year-old category is calculated as 100 minus the sum of the younger categories. For the UCC data, we compute the proportion of equipment purchases by firms in each age category.

Table A6
Nonincidental Sample Selection

	(1)	(2)
	Selected In = 1	
	Machine Age ≤ 10 Only	
ln(1+Machine Age)	0.006**	-0.003
	[0.003]	[0.003]
Observations	247,717	247,717
R^2	0.005	0.088
Year FE	Y	Y
Machine Type FE		Y

Notes. This table documents the relationship between sample inclusion/exclusion and machine age. The sample consists of the set of machines which are ten years old or less for which we observe a wholesale transaction. The dependent variable, *Selected In*, is a dummy set equal to one if the machine reappeared as a retail sale within one year of being reported as part of an equipment dealer's wholesale floor-plan financing. *Machine Age* is the difference between the original manufacture year and the year of the transaction. Standard errors clustered at the machine type level are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A7
Examples of Heavy/Light and Short-lived/Long-lived Equipment Types

Low weight-to-value equipment	Modal Industry (SIC-3 description)
OFF ROAD TRUCK	Bituminous Coal and Lignite Mining
MFR LASER	Fabricated Structural Metal Products
CRAWLER CRANE	Heavy Construction, except Highway
BLASTHOLE DRILL	Miscellaneous Special Trade Contractors
HORIZONTAL MACHINING CENTER (3-4 AXIS)	Industrial Machinery, NEC
High weight-to-value equipment	
PERSONNEL LIFT	Heavy Construction, except Highway
BREAKER/HAMMER	Miscellaneous Special Trade Contractors
C3 L/L PALLET WR (PALLET TRUCK)	Groceries and Related Products
AUGER/DRILL	Landscape and Horticultural Services
BROOM	Highway and Street Construction
Short-lived equipment	
C2 SWINGRE NISLE (SWING FORKLIFT)	Public Warehousing and Storage
WELDER (LASER)	Miscellaneous Manufacturing Industries
C3 L/L PALLET WR (PALLET TRUCK)	Groceries and Related Products
PIERCING MOLE	Heavy Construction, except Highway
LOAD HAUL DUMP	Coal Mining Services
Long-lived equipment	
SCREW MACHINE	Screws, Bolts, Nuts, Rivets, and Washers
BORING MILL	Industrial Machinery, NEC
DRAGLINE (CRANE)	Miscellaneous Special Trade Contractors
ENGINE LATHE	Industrial Machinery, NEC
PIPELAYER	Heavy Construction, except Highway

Notes. This table compiles common examples of equipment types based on their log(weight)-to-value and market longevity. Low (high) weight-to-value examples are chosen from the first (tenth) decile of log(weight)-to-value based on the largest contribution to the *Local Vintage Capital (SIC-3)* measure. Short-lived (long-lived) equipment examples are equipment types with the shortest (longest) market longevity. In each category, we limit reported equipment types to one from each broader equipment category. This affects only high weight-to-value equipment, where there would otherwise be two equipment types in the broader "Miscellaneous Attachments" category, and long-lived equipment, where there would be two equipment types in the broader "Cranes" category. Modal industries (three-digit SIC) for each equipment type are also reported.

Table A8
Local Vintage Capital and Machine Choice Extension

	(1) Chosen Machine = 1
ln(1+Local Vintage Capital MT) (std.)	0.013
	[0.014]
ln(1+Local Vintage Capital MT) (std.) × Heavy	0.045**
	[0.019]
ln(1+Local Vintage Capital MT) (std.) × Long-lived	0.075***
	[0.014]
Observations	361,303
R^2	0.487
County-Year-Equipment Category FE	Y
Machine Type FE	Y

Notes. This table extends Table 6 in which we examine the equipment purchase choice of firms in response to local vintage capital supply by including interactions for both *Heavy* and *Long-lived* capital in the same specification. For each realized transaction, we construct a set of "pseudo transactions" by pairing the buyer with all the other possible equipment types under the same equipment category. The unit of observation is a potential machine purchase, and the dependent variable (*Chosen Machine*) is equal to one for the actual machine purchased and zero for the pseudo transactions. The sample includes only observations in which the purchasing firm is young (three years old or less) and includes only *Heavy* and *Light* equipment so that the *Heavy* interaction compares heavy to light equipment, as in column (4) of Table 6. *Local Vintage Capital MT* varies at the machine type-county-year level and is defined in Section 4.1 based on local transaction histories. (std.) denotes that the variable is standardized to have a mean of zero and standard deviation of one for interpretation. Standard errors are double clustered at the industry (three-digit SIC) and county level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A9
Local Vintage Capital and Start-up Investment Extension

Panel A: Heavy vs. Light Machines within Long-lived Equipment

	(1)	(2)	(3)
		ln(1+Investment(1,3))	
	Total Machines	Machine Types	New Machines
ln(1+LVC Heavy Long-lived) (norm.)	0.197***	0.151***	0.131***
	[0.054]	[0.043]	[0.038]
ln(1+LVC Mid-weight Long-lived) (norm.)	0.146***	0.120***	0.085***
	[0.048]	[0.038]	[0.029]
ln(1+LVC Light Long-lived) (norm.)	0.042*	0.036*	0.020
	[0.022]	[0.019]	[0.015]
ln(1+LVC Short-lived) (norm.)	-0.064	-0.054	-0.027
	[0.075]	[0.060]	[0.054]
Observations	71,722	71,722	71,722
R^2	0.231	0.238	0.203
County-Year FE	Y	Y	Y
Industry (SIC-3)-Year FE	Y	Y	Y
p-value of *Heavy* vs. *Light*	0.011	0.021	0.008

Notes. This table examines the relationship between start-up investment activity and local vintage capital availability as in Table 8. The sample includes only investment by young firms (aged three years and younger) at the time of their first machine acquisition. The outcome variables capture the natural log of (1+) investment during the period one to three years after the initial investment, measured three ways. *Total Machines* measures investment as the total number of equipment acquisitions. *Machine Types* captures the number of different equipment types acquired. *New Machines* captures the total number of acquisitions of brand new equipment. *Local Vintage Capital SIC-3*, measured at the time of the firm's first machine acquisition, varies at the industry-county-year level and is defined in Section 4.1 based on local transaction histories. In each panel, this variable is partitioned into components. Panel A replicates the regressions in Panel B of Table 8 with *LVC Long-lived* further partitioned into heavy, mid-weight, and light components, as defined in Section 4.3. The comparison of *Heavy* vs. *Light* is therefore within *Long-lived* equipment, holding fixed the effect of market longevity. (norm.) denotes that the components have been normalized so that a one-unit change in each component corresponds to a one-standard-deviation change in *ln(1+Local Vintage Capital SIC-3)*, making all coefficients in the table directly comparable. (See Appendix Section A.2 for a detailed description). Panel B replicates the regressions in Panel C of Table 8 with *LVC Mid-weight* further partitioned into long-lived and short-lived components. The comparison of *Long-lived* vs. *Short-lived* is therefore within *Mid-weight* equipment, holding fixed the effect of equipment mobility. Standard errors are double clustered at the industry (three-digit SIC) and county level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Long-Lived vs. Short-Lived Machines within Mid-weight Equipment

	(1)	(2)	(3)
		ln(1+Investment(1,3))	
	Total Machines	Machine Types	New Machines
ln(1+LVC Heavy) (norm.)	0.173***	0.129***	0.118***
	[0.057]	[0.045]	[0.037]
ln(1+LVC Mid-weight Long-lived) (norm.)	0.142***	0.117***	0.083***
	[0.046]	[0.037]	[0.030]
ln(1+LVC Mid-weight Short-lived) (norm.)	-0.055	-0.049	-0.045
	[0.080]	[0.066]	[0.051]
ln(1+LVC Light) (norm.)	0.040*	0.035*	0.021
	[0.022]	[0.019]	[0.016]
Observations	71,722	71,722	71,722
R^2	0.231	0.238	0.203
County-Year FE	Y	Y	Y
Industry (SIC-3)-Year FE	Y	Y	Y
p-value of *Long-lived* vs. *Short-lived*	0.036	0.032	0.015

Table A10
Local Vintage Capital and Start-up Employment Extension

	(1)	(2)
	ln(1+Start-up Employment (t=2))	
ln(1+LVC NAICS-2 Heavy Long-lived) (norm.)	2.363*	
	[1.136]	
ln(1+LVC NAICS-2 Mid-weight Long-lived) (norm.)	0.691***	0.609***
	[0.163]	[0.175]
ln(1+LVC NAICS-2 Light Long-lived) (norm.)	0.459	
	[0.270]	
ln(1+LVC NAICS-2 Short-lived) (norm.)	0.031	
	[0.252]	
ln(1+LVC Heavy) (norm.)		3.002**
		[1.427]
ln(1+LVC Mid-weight Short-lived) (norm.)		-0.358**
		[0.146]
ln(1+LVC Light) (norm.)		0.452*
		[0.255]
Observations	232,510	232,510
R^2	0.721	0.722
County-Year FE	Y	Y
Industry (NAICS-2)-Year FE	Y	Y
p-value of *Heavy* vs. *Light*	0.058	
p-value of *Long-lived* vs. *Short-lived*		0.000

Notes. This table examines the relationship between start-up employment and local vintage capital availability as in Table 9. The unit of observation is a county-industry-year, where industry is two-digit NAICS. *Start-up Employment (t=2)* is the number of new jobs created by start-ups from $t = 0$ to $t = 2$ as reported in the Census LEHD QWI data. *Local Vintage Capital NAICS-2*, measured at $t = 0$, varies at the industry-county-year level and is defined in Section 4.1 based on local transaction histories. In each column, this variable is partitioned into components. Column (1) replicates the regression in column (3) of Table 9 with *LVC NAICS-2 Long-lived* further partitioned into heavy, mid-weight, and light components, as defined in Section 4.3. The comparison of *Heavy* vs. *Light* is therefore within *Long-lived* equipment, holding fixed the effect of market longevity. (norm.) denotes that the components have been normalized so that a one-unit change in each component corresponds to a one-standard-deviation change in *ln(1+Local Vintage Capital NAICS-2)*, making all coefficients in the table directly comparable. (See Appendix Section A.2 for a detailed description). Column (2) replicates the regression in column (2) of Table 9 with *LVC NAICS-2 Mid-weight* further partitioned into long-lived and short-lived components. The comparison of *Long-lived* vs. *Short-lived* is therefore within *Mid-weight* equipment, holding fixed the effect of equipment mobility. Standard errors are double clustered at the industry (two-digit NAICS) and county level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.