Young Firms, Old Capital*

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We explore the interaction of capital reallocation and entrepreneurship activities. Across a broad range of equipment types and industries, young firms are the predominant buyers of vintage physical capital previously owned by older local firms. The pattern is strongest when financial constraints are most likely to bind. We argue that this pattern drives a mutually-beneficial relationship between co-located young and old firms through local used capital markets. The investment choices, growth, and job creation by start-ups depend on vintage capital supplied by older local firms. Meanwhile incumbents accelerate capital replacement in the presence of young firms.

JEL Classification: L26, E22, G31

Keywords: Capital Reallocation, Entrepreneurship, Investment, Agglomeration

* *This version*: July 29, 2020. We thank seminar and conference participants at Chicago Booth, Colorado Finance Summit, Duke/UNC I&E Research Conference, FDIC, Federal Reserve Bank of Philadelphia, Federal Reserve Board, GSU Conference on Financing Tangible and Intangible Capital, HEC Workshop on Entrepreneurship, Junior Entrepreneurial Finance and Innovation Workshop, Kellogg, Pittsburgh, Princeton, SFS Cavalcade, Syracuse, Tilburg, Toronto, Utah, Washington St. Louis Corporate Finance Conference, and Yale (Applied Micro). We also thank Tony Cookson, François Derrien, Jason Donaldson, William Mann, Sahil Raina, Adriano Rampini, Xinxin Wang, and Liu Yang for detailed comments. Huijun Sun and Ran You provided excellent research assistance. Yale International Center for Finance provided research support. We thank Erik Gilje for generously sharing data on county-level shale oil shocks. All errors are our own.

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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. Regarding the former, 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). Regarding the latter, the reallocation of capital—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: that young firms are the predominant buyers of old capital seasoned by older, established firms in the same county. We argue that this pattern of 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 1.5 million transactions covering 70,000 models of machines used across a broad range of industries. Across a wide range of industries and equipment types, young firms deploy older capital, whereas old firms are the predominant investors in new capital. This correlation is not obviously explained by selection related to omitted machine or firm characteristics, and 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. Similar patterns emerge in separate samples covering machine tools, woodworking tools, printers, copiers, lift trucks, and machines used in logging and construction and are both statistically and economically significant in more than 80 percent of industries. We also consider the effects of endogenous sample selection and find limited evidence that this contributes to the finding.

Given the observed reallocation dynamic, what features of older machines make them relatively more 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 higher future user cost. Consistent with this theory, Benmelech and Bergman (2011) find airlines in countries with stronger creditor protections, and hence more ample credit availability, invest in newer vintages of aircraft for their fleets.

To evaluate the extent to which financial constraints 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).

Given the potential importance of used capital to young firms, it makes sense to ask whether that supply needs to be locally provided. If so, this might suggest important geographic links between young and old firms, as purchasers and providers of used capital respectively. Using our ability to track machines across users via their serial numbers, we confirm that trade in used machines is largely a local activity, and increasingly so as capital ages. The suggestion of gains from trade across young and old firms in the same locality motivates the second section of the paper, which asks how the opportunity for used capital purchases by young firms from local older firms (and conversely, the opportunity for old firms to sell used capital to local younger firms) affects their investment choices, and perhaps supports returns to co-location.

To explore these ideas, 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 i provides a measure of the latent supply of k year-old used machines potentially available in county i 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. We then investigate whether 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 in a county may be correlated with young firm dynamics for a variety of reasons. For example, long-lasting industry booms may lead both to increased start-up activity and increased supply of used capital. Alternatively, as our measure of local vintage capital is a lagged version of new equipment transactions, we may be picking up an effect driven by robust new equipment markets.

To address these alternative hypotheses, our identification rests on differential effects of local vintage capital along three dimensions. First, we benchmark the effect on young firm activity against the effect on older firms. If the effect is driven by availability of new capital, we would expect old firms to be more impacted, given their relative reliance on new equipment. Second, we exploit variation in capital mobility determined by the physical characteristics of machines. Specifically, we show that machines with a high weight-to-value ratio 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 market longevity of machines. If young firm investment is driven by old capital availability, then we should find little effect among machine types that infrequently transact when old.

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 monotonically 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 would seem to lend credence to anecdotes common among entrepreneurs about the sensitivity of early decisions to the local availability of inputs. As a prominent example, the iconic start-up Ben and Jerry's chose to make ice cream after finding a used ice cream truck and freezer for sale locally, but only after abandoning their initial plan to make bagels due to their inability to find affordable used bagel machines.[1]

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-quarter employment, as a measure of 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.

[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.

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 demand for 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 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), labor (Brown and Medoff, 2003; Ouimet and Zarutskie, 2014), and business focus (Ewens, Nanda, and Rhodes-Kropf, 2018). Our paper brings capital investment, another key component in firms' production functions, to the discussion. The documented investment patterns also link our paper to studies on capital investment and replacement (Gavazza, 2011a,b).

The fact that local capital reallocation links firms in the same industry may also be relevant to our understanding of agglomerative forces in the urban economy. Agglomeration is both a feature of any modern economy and a robust growth driver (Davis, Fisher, and Whited, 2014). The Marshallian view (Marshall, 1890) of agglomeration highlights rationales like labor market pooling, customer-supplier interactions, and knowledge spillovers (Duranton and Puga, 2004; Ellison et al., 2010; Kerr and Kominers, 2015), arising from the returns to minimizing transport costs for workers, goods, or ideas, respectively (Ellison et al., 2010). We complement this view by highlighting a new motivation for agglomeration: minimizing transport costs of physical capital. Firm linkages through capital reallocation suggest specific predictions about the importance for co-location among young and old firms.

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 in 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 Dun & Bradstreet provided information on the firm industry and age.

The complete data set includes nearly 6 million observations covering more than 150,000 models of equipment, including construction equipment, copiers, lift trucks, logging equipment, woodworking tools, and machine tools. The equipment is coded into 112 broad categories based on functionality (e.g., cranes), which are then coded into 332 detailed equipment types based on their more specific characteristics (e.g., crawler crane, truck crane). For each of these equipment types, 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.

Given our goal to link equipment reallocation with geographic agglomeration, 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 to local credit conditions by tracking, for each county-quarter, the exposure to shale-discovery-driven windfalls through the banking network.[2] 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 age groups, allowing us to observe local start-up activity.

[Insert Table 1 About Here.]

For our initial tests, we focus on the sample of machine purchases for which we observe both firm age and machine age. Although there are 4.3 million total purchase observations (1.5 million observations are leases, which we will include in later tests), firm age coverage is roughly 60 percent and machine age coverage is 75 percent. These restrictions leave us with 1.5 million purchase observations. Panel A of Table 1 reports summary statistics. The mean (median) age of a machine in the UCC transaction data is four years (one year). The mean (median) firm age in our sample is 22 (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 $70,000, while the 25th and 75th percentiles of equipment value are $16,061 and $92,921. Panel B reports the industry distribution of these equipment purchases. Construction firms are important purchasers of equipment in our sample, accounting for 48.6 percent of the observations, but equipment transactions span a wide variety of industries.

[2]See Appendix A.1 for more details.

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 5.7 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 4.0 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).

[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 $4,367 per year. Meanwhile, the median acquisition value of a firm in its first year is $44,091. The roughly 2.5-year change in average machine age going from a start-up to a fully mature firm implies a $10,918 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.[3] To visually isolate

[3]For example, firms that purchase copiers are on average 23 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.

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 have transactions in at least ten different years and 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 5.1 years old, between the average age of equipment purchased by zero and by one-year-old firms in Figure 2. By the time firms purchase their sixth piece of equipment, the average equipment age has fallen to 3.5 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 (4-digit SIC level) and equipment-type-by-equipment-type coefficients from a regression of machine age on firm age.[4] 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 176 industries, we find that the relationship between young firms and old capital holds at the one percent level for 135 industries and at the ten percent level for 148 industries. The relation is positive and significant at the ten percent level for only 8 industries. Of the 117 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 100 types.

[4] We require at least 1,000 machine transactions in each industry and for each equipment type.

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 a complete set of equipment purchases i using the following model:

$$\log(1 + Machine\ Age_i) = \beta \cdot \log(1 + Firm\ Age_i) + \delta_{FE} + \varepsilon_i. \tag{1}$$

In these regressions, each observation includes information on the purchasing firm, its industry (3-digit SIC code), transaction year, machine type (e.g., compact utility tractor), and the machine itself. Both machine age and firm age are measured as the logarithm of one plus age.[5] 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-by-year and industry 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 is large. Moving from a start-up to the mean age firm (22 years), the average age of machines decreases by 32 percent, or roughly 1.8 years, relative to the average start-up machine age of 5.7 years old. This corresponds to an approximate reduction in machine value (using EDA estimates) of $7,858, or 18 percent of average 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

[5] In Appendix Table A1, we show that the results in Table 2 are qualitatively and quantitatively similar if we transform the age variables using an inverse hyperbolic sine operator.

picking up this firm-asset matching outcome. The result in column (2), with an economically large and statistically significant coefficient, suggests 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 the machines that we can follow, the average difference in age between the seller and buyer is six years—the owner age shrinks by 28 percent with each reallocation.

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 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. We test this idea by interacting a cross-sectional 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-by-quarter variation in bank liquidity driven by deposit windfalls in distant branches of local banks related to shale oil discoveries.[6] Bank liquidity shocks are aggregated to the county-year level

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

to come up with geographic variation in access to credit. We characterize better credit as a dummy for above median values of the size of the measured shale-driven liquidity shock. We then augment the model in Equation (1) with an interaction term of firm age and the shale shock indicator. The results are reported in Table 3 columns (1) and (2), showing that young firms' preference for old capital decreases by about 20 percent with better credit access.[7] This suggests a prominent role for financial constraints in the allocation of older capital.

[Insert Table 3 About Here.]

In columns (3) and (4), we turn our attention to the form of the financing contract. Though more than 70 percent of the transactions in our data involve loans for equipment purchase, there are also transactions involving leased equipment. While leases and loans share similar economic characteristics, Eisfeldt and Rampini (2009) argue that the distinction in legal ownership results in easier repossession and therefore greater pledgeability for leased equipment, which eases financial constraints. Consistent with a financial constraints motive, we find limited evidence that young firms use older capital when they lease it.

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 column (5), we provide a more direct test of the technological preference explanation. We replace machine age with "model age," defined as the difference between the year of the transaction and the year of model introduction.[8] We restrict the sample to the subset of transactions 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 this regression is economically negligible while being relatively precisely estimated.

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

[8] The median production life for an equipment model in our data is ten years.

3.4. Nonincidental Sample Selection

So far, we have avoided any discussion of sample selection—i.e., the data generating process that allows us to observe equipment acquisitions together with buyer characteristics. Because our data are generated as a result of secured debt financing with liens perfected under the UCC, exclusion from the data is not random, but instead will 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 easily 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.[9] Regarding UCC selection on firm age, in Appendix Table A2, we report the proportion of UCC machine purchases made by firms in different firm-age groups alongside the proportion of employment by firms in those same age groups using selection-free Census 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). While new machines benefit from manufacturer financing relative to used machines (Murfin and Pratt, 2019), supporting their more frequent sample inclusion, variation in financing status across machine age among used machines is not obvious. Meanwhile, 60 percent of equipment transactions are for machines at least one year old, so these machines will be of most interest to us in terms of understanding the typical relationship between machine and firm age.

To estimate the sign of machine age in the selection equation, we need a sample of

[9]To induce a bias consistent with Heckman (1979), both factors correlated with firm and machine age must enter into the selection equation.

machines for which we can observe the complete information on whether each was selected into UCC. We exploit a subset of UCC filings that are flagged by the data provider as wholesale acquisitions, primarily floor-plan financing for dealer inventory. These transactions are useful if we assume that when dealers borrow against machines in inventory, those machines will subsequently be sold to retail buyers. For these machines, 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.

[Insert Table 4 About Here.]

In Table 4, we model the selection equation, examining whether a wholesale transaction was followed by a subsequent sale over the next year—that is, selected into the sample. We include a dummy for new versus used machines as well as a non-binary age variable, allowing the new versus used margin to impact selection differently from variation in age within used machines. The table suggests that brand new machines may be more likely to be selected into our sample. However, among used machines, the relationship between age and selection is economically tiny and not distinct from zero.

Given that machine age appears to influence financing (and hence selection) only at the new versus used margin, how should we interpret our results? To see what the results would look like absent these selection effects, we can re-estimate the regressions from Table 2 among used machines—the subset for which age appears unimportant for selection. Because the regression of interest requires that we truncate machine age, Table 4 Panel B estimates a truncated regression model to deal with the bias associated with truncated left-hand-side variables. Consistent with selection biases being small, a comparison of the main effects in columns (1) and (2) versus (3) and (4) yields little difference in effect size.

4. Old Capital, Local Economic Activities, and Agglomeration

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 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. If true, 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. Perhaps more importantly, it would suggest gains to co-location among young and old firms and provide a novel channel for the returns to geographic agglomeration.

To evaluate the conjectures 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 (unused) 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 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).

The procedure above gives us a measure of old capital availability at the county $\times$ equipment-type $\times$ year level. For some of our tests, we will be interested in the total amount of old equipment available to a firm in a particular industry. The measure of industry supply aggregates the equipment-type-level variable up to the industry level for all the equipment types purchased by a given industry, weighting based on the relative frequency of purchase. We describe this in more detail when we use the industry measure in Section 4.5.

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. This is critical to our identification, which relies on geographic variation in used capital, but also suggests an empirical question: how local is trade in used capital?

Given the ability to track machines by way of their serial number over subsequent trades, our data provide a unique setting to answer this question. 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 5 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 more than 75 percent occurs within 200 miles. Figure 5 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 Table 5, we regress the logarithm of moving distance on machine age and on the number of times a machine has been traded. The regressions include fixed effects for industry, machine type, and the locations of buyers and sellers (separately), allowing us to control for variation in trade activity that may relate to a location's remoteness. In each specification, 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 1.7 percentage point higher probability of being traded within the same county, which is an 8.5 percent increase from the base rate.

[Insert Table 5 About Here.]

These new facts support our use of geographic variation to identify the effects of used capital supply on entrepreneurial activity, but they also point to a path to sharper identification of the mechanism at work.

4.3. Identifying Variation

Young firms' preference for old capital suggests a testable hypothesis: does local vintage capital causally affect young firm investment? Our measure of local vintage capital, however, could also be correlated with young firm investment through confounding economic activity. 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. 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 variation in mobility of physical capital. The fact that older capital trades more locally is consistent with the Alchian and Allen Theorem (Alchian and Allen, 1964), who 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.

Figure 6 plots machine transportation costs as a function of weight, obtained from the heavy equipment shipping broker uShip.[10] As the figure shows, shipping costs vary closely with the log of weight, indicating that proportional shipping costs depend on $log(weight)/value$. To estimate 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.

[Insert Figure 6 About Here.]

We conjecture that our measure of weight-to-value ratios should provide a strong proxy for constraints to the locality of trade. 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). Of course, a necessary condition is that our measure provides a strong first-stage in predicting the distance a machine travels after a typical sale. Figure 7 confirms this is the case. The figure presents a binned scatter plot of the average logged trade distance against deciles of weight-to-value, conditional on the fixed effects from Table 5.[11] Moving from the lightest to the heaviest

[10] See Appendix A for details on the construction of this plot. Data were acquired from `www.uship.com`.

[11] Note that we don't include Machine Type fixed effects, as they would subsume the weight-to-value measure.

machines reduces trade distance by roughly 35 percent. The pattern is monotonic with the exception of the tenth decile, which has a moving distance roughly equal to the eighth decile. We classify the top three deciles of weight-to-value as *heavy* machines, the bottom three 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 variation 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 that are actually available to trade after year 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 the 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*. One caveat is in order. Most equipment types in our sample have robust used markets beyond five years. Only 11.7 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 this instrument has very little relationship to the weight-to-value measure. The average weight-to-value decile among short-lived types is 7.1, while the average among long-lived types is 5.3, indicating slightly negative correlation across the two measures.

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, which we define throughout the paper as firms aged three years and younger, against the effect on mature firms. While a relationship between local old capital and entrepreneurial investment 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 with a test of how the supply of old machines shapes firm investment choices, conditional on a firm investment occurring. To this end, in Table 6, we estimate a choice model of machine purchase based on variation in used capital supply. Conditional on a purchase being made in a given year-county, we assume a potential choice set for that transaction consisting of all of the equipment types within the same broader equipment category. We then test whether the availability of old equipment influences the specific choice of equipment from among alternatives in the same equipment category.

Returning to the example from earlier, consider that 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. Equipment type and sub-category classifications are provided by EDA and defined by machine function. On average, each equipment category (containing more than one equipment type) contains 4.76 equipment types, suggesting an unconditional purchase probability within the choice sample of 21 percent.

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

$$\begin{aligned} I(Bought_i) =& \beta \cdot \log(1 + LocalVintageCapital_i) \times YoungFirm_i + \\ & \beta' \cdot \log(1 + LocalVintageCapital_i) + \beta'' \cdot YoungFirm_i + \delta_{FE} + \varepsilon_i. \end{aligned} \tag{2}$$

$I(Bought)$ is a dummy variable that takes the value one for the specific equipment type actually purchased. $LocalVintageCapital$ is at the equipment type-county-year level, capturing variation in the latent supply of each type of equipment. $YoungFirm$ is a dummy variable indicating whether the buyer is younger than three years old.

Of course it won't be surprising that supply affects the eventual equipment choice. Instead, our identification depends on the differential effects of the latent supply of local capital across three dimensions, beginning with firm age and following with machine weight-to-value and machine longevity. We discuss our predictions for the three interactions in turn, beginning with firm age.

Imagine two Durham County lumberjacks—one young, one old—are in the market for forestry equipment in 2010. They are presented with the same opportunity to choose from various equipment types. Our first hypothesis is that young firms' decisions are more sensitive to old capital supply. In order for our model to approach this thought experiment, our specifications include fixed effects at the equipment category-county-time level (e.g., forestry equipment-Durham-2010). This fixed effect structure captures the thought experiment described above and ensures we are not capturing slow moving industry booms or local economic trends correlated with supply. We also control for equipment type fixed effects (where "types" are a subset of the broader equipment category) to absorb machine characteristics correlated with supply. Standard errors are clustered at the buyer-equipment category-year level, taking into account that each buyer's decisions over a set of equipment types within the same category are negatively correlated. The coefficient of primary interest from this regression is that of the interaction between $Young$ and $LocalVintageCapital$.

[Insert Table 6 About Here.]

Table 6 presents the results. In column (1), we report the baseline sensitivity of all firms to our local vintage capital measure. The supply variable has been standardized, so that a one standard deviation shift in supply of a given machine type increases its odds of being chosen by roughly 0.05, compared to a sample mean of 0.21. In column (2), we compare the sensitivity to local vintage capital across young and older firms. Firms younger than three years old are statistically more sensitive to old capital. We defer our discussion of the economic magnitude until later.

While our analysis is designed to test the hypothesis that old capital availability induces young firms to adjust their investment program, an alternative interpretation 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 (e.g., the presence of a local equipment dealership).

To separately identify these competing explanations for the results in columns (1) and (2), we introduce two ancillary predictions that would follow from used equipment supply causing investment choice but not from the alternative explanations described above. First, given our finding that weight-to-value is a determinant of the locality of secondary market trade, a causal effect of used capital requires that the used supply of physically heavier equipment will have a larger effect on young firm behavior. In contrast, when geographic proximity is irrelevant to availability, our local measure of capital supply will only serve as a noisy measure of national supply, the effects of which should be absorbed by time dummies.

Second, the effects of vintage capital presume a machine's ability to remain marketable for the five years after its introduction as a new machine to the area. Hence, we introduce a measure of equipment longevity based on the age distribution of market activity. We predict a null effect of equipment supply for machine categories that, on average, do not trade after year five.

In columns (3) and (4), we test these hypotheses on the sample of young firms, adding an interaction between local vintage capital and (i) a dummy variable for *Heavy* equipment and (ii) a dummy variable for *LongLived* equipment (as defined in Section 4.3). In each case, the results are consistent with the physical proximity of vintage capital being important, with larger effects for heavy equipment constrained to trade locally and no observable effect for machines that have limited used marketability after the first five years of life. In contrast, 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. Yet we find zero supply effects for machines with limited market longevity.

[Insert Figure 8 About Here.]

Figure 8 takes these three dimensions into account (firm age, machine weight, and longevity) 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 $LocalVintageCapital$ across age groups for heavy and long-lived machines, against the same responses for the placebo groups (light and short-lived).

Several facts jump out. First, for light equipment and equipment with limited market longevity, we find zero effects across all firm age groups. In contrast, we find significant effects for all firm age groups among heavy and long-lived equipment. And (only) among these equipment groups, the effect is monotonically declining with firm age. For start-ups, the effects are notable. Given the unconditional probability of choosing a machine of 0.21, a one standard deviation increase in vintage capital supply raises that probability by 0.09 for heavy equipment and 0.07 for long-lived machines. These effects are large both compared to small effects for the oldest firms (0.02 and 0.03) and the null effects observed for light and short-lived placebo equipment groups.

4.5. Local Vintage Capital and Young Firm Growth and Entry

Table 6 suggests that, conditional on investing, young firms' choices of equipment depend on local vintage 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 investment alternatives. Or does it have a meaningful impact on a firm's growth trajectory during its early years?

To examine this question, we study the extensive margin of young firm investment. We focus on the sample of firms that made at least one equipment investment during their first three years. We then estimate how the investment dynamics following the initial investment are influenced by local vintage capital availability. Specifically, we estimate the following regression:

$$\log(1 + Investment_{i,t+1,t+3}) = \beta \cdot \log(1 + LocalVintageCapital_{I,i,t}) + \delta_{FE} + \varepsilon_{i,t}. \qquad (3)$$

$Investment_{i,t+1,t+3}$ captures investment of firm i between one and three years after the initial investment 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.[12] $LocalVintageCapital_I$ (subscript denotes "industry") is defined at the county-industry-year level to capture the total amount of old equipment available to the start-ups in the county-industry at the time of the initial investment. To transform equipment-level supply into industry-level variation, we aggregate the equipment-type variable described in Section 4.1 at the 3-digit SIC industry level based on the distribution of industries that acquire each machine type over the entire sample. 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 off different values, we measure vintage capital based on equipment values (as new) rather than equipment counts. Our main independent variable is the log of $1{+}LocalVintageCapital_I$, which we standardize to ease the interpretation of our estimates. We include combinations of county-year and industry-year fixed effects to absorb local and industry growth trends and cluster our standard errors at the industry and county levels.

[Insert Table 7 About Here.]

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

Table 7 Panel A presents the results. Column (1) shows that young firms with better access to old capital invest more in additional equipment between one and three years after their initial investment. A one-standard-deviation increase in the amount of local used capital leads to a 7.4 percent increase in subsequent capital investment.

While the result in column (1) is 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 column (2) we examine the total machine types that a young firm invests in between one and three years after its initial investment. We find that the supply of used equipment at the time of initial investment results in a broader array of equipment purchases in the future. A one-standard-deviation increase in the local supply of used capital at the time of a young firm's initial investment leads to a 6.0 percent increase in the number of equipment types a firm invests in over the ensuing years.

In column (3) 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 used capital supply resulting in a 4.0 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 Panel A 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. Meanwhile, we've shown that machines with a high weight-to-value ratio are more constrained to trade locally. If locally available used capital causes entrepreneurial investment, we would expect the local supply of heavy equipment to impact new firm investment more than the local supply of lighter, more mobile equipment. Other potential mechanisms linking investment to our measure of vintage capital supply—for example, local industry booms with lagged effects on start-ups—have ambiguous predictions regarding the interaction with equipment weight. As a result, the comparison of light versus heavy equipment supply on start-up behavior may be useful in parsing alternative interpretations.

To test these predictions, we cannot simply interact $LocalVintageCapital_I$ with a weight-to-value categorical variable, since $LocalVintageCapital_I$ is an industry-level measure that includes all equipment types. Instead, we partition $LocalVintageCapital_I$ into heavy, medium, and light components. $LVCHeavy_I$ is the local, industry supply of equipment from the top three deciles of our weight-to-value measure, while $LVCLight_I$ includes equipment from the bottom three deciles, and $LVCMedium_I$ includes equipment from the middle four deciles. Note that $LocalVintageCapital_I = LVCHeavy_I + LVCMedium_I + LVCLight_I$. We then replace the log of $LocalVintageCapital_I$ from Equation 3 with the log(1+$LVCHeavy_I$), log(1+$LVCMedium_I$), and log(1+$LVCLight_I$) so that we can compare coefficients across these components of total vintage capital.

This decomposition introduces a technical issue. Heavy equipment makes up 17.4 percent of the value of old equipment available in an industry × county × year on average, while medium and light equipment make up 46.7 percent and 35.8 percent, respectively. Consequently, a one percent increase in heavy equipment represents only a 0.174 percent increase in total available equipment, while a one percent increase in light equipment represents a 0.358 percent increase in total equipment. Under the null hypothesis that all equipment has an equal relationship with entrepreneurial investment regardless of its weight-to-value, we would see a coefficient on $LVCLight_I$ (β_{light}) roughly twice as large as the coefficient on $LVCHeavy_I$ (β_{heavy}). In order to meaningfully compare coefficients, we need to put things on a level playing field. To do this, we multiply $LVCHeavy_I$ by 0.174 (which scales β_{heavy} up by 1/0.174), and similarly for $LVCMedium_I$ and $LVCLight_I$. The interpretation of the resulting β_{heavy} would be the effect of a one percent change in *total* vintage capital coming from additional *heavy* vintage capital (and similarly for medium and light capital).[13] Finally, to make the interpretation comparable to Panel A, we divide each component of vintage capital by the standard deviation of $LocalVintageCapital_I$. Thus, β_{heavy} represents the impact of a one standard deviation

[13]Note that, under the null hypothesis, the effect of heavy capital on young firm investment is equal to the

change in total vintage capital coming from an increase in heavy vintage capital.[14]

The results are shown in Panel B. In column (1), we find that a one standard deviation increase in vintage capital coming from additional heavy capital increases young firm investment by 17.4 percent. For increases in equipment coming from additional medium weight-to-value capital, young firm investment increases by 11.2 percent, while investment changes by a statistically insignificant 2.8 percent with additional light capital. An F-test rejects equivalence of β_{heavy} and β_{light} with a p-value of 0.003. 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, is 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 less than one 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 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 benchmark. 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 these predictions, we repeat the process described above for weight-to-value in

effect of total vintage capital (from Panel A) multiplied by the heavy capital proportion:

$$\begin{aligned}\beta_{heavy} &= \frac{\partial y}{\partial log(LVCHeavy_I)} \\ &= \frac{\partial y}{\partial log(LVC_I)} \cdot \frac{\partial log(LVC_I)}{\partial log(LVCHeavy_I)} \\ &= \beta_{LVC_I} \cdot \frac{LVCHeavy_I}{LVC_I}\end{aligned}$$

The same is true for mid-weight or light equipment. This suggests the scaling approach we adopt. Simulation evidence confirms that this approach delivers correct distribution of F-tests under the null that all types of equipment have an equal effect on entrepreneurial investment.

[14] This last step, of course, has no effect on the t-stats for individual coefficients nor on the F-stats for comparing coefficients.

terms of scaling the individual components of total vintage capital. Short-lived machines comprise 19.2 percent of total vintage capital, with the remainder coming from long-lived machines. Across all dependent variables, only the availability of long-lived machines impacts future young firm investment. In each case, the relationship with short-lived equipment is insignificantly negative, though F-tests are only marginally significant due to how imprecisely the effect of short-lived equipment is estimated.

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 Panel A, interacting an indicator for young firms with $LocalVintageCapital_I$. 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 the $LocalVintageCapital_I$ variable 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) reveals no 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 next section.

4.6. Old Capital and New Firm (Job) Creation

Table 7 indicates 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 among firms in different age categories. Our dependent variable is log(1+employment) in firms aged zero to one year. The independent variables are the local vintage capital variables from Panels A through C of Table 7, except that the industry level is now 2-digit NAICS to conform to the LEHD data. The independent variables are 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?

We report the results in Table 8. The coefficient in column (1) suggests that a one standard deviation increase in local used capital results in 18.5 percent more employment in start-ups. In column (2), we break $LocalVintageCapital_I$ into components based on equipment weight-to-value. The results suggest that less mobile equipment has a stronger impact on local start-up employment, with the lightest equipment having no discernible effect on new firm employment. An F-test rejects equivalent effects of heavy and light equipment with a p-value of 0.077. Column (3) indicates 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 0.032.

[Insert Table 8 About Here.]

As young firms are a significant driver of employment growth (Adelino et al., 2017), the results in Table 8 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 Table 7. 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.

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 acquiring 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. To ensure we are not capturing the same firms in the left and right hand sides, we limit observations on machine replacement to machines purchased by incumbents, defined as firms more than three years old. The unit of observation in this analysis is a piece of physical equipment acquired by an incumbent (which can then either be replaced or not). Each of these purchases can be characterized by a machine type, the location at the county level, the industry of the firm, and the year of original acquisition. The dependent variables capture whether the equipment is replaced (sold with a similar machine bought) over three, four, and five year time horizons.

$YoungFirmsShare$ is the key independent variable and 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) in industries that are active users of a given equipment type. This variable is calculated for each machine type in each county-year. For each machine type, we measure the frequency with which it is purchased in all possible industries (2-digit NAICS) to calculate industry weights (e.g., 60 percent of excavators may be used in construction and 40 percent in logging). For each equipment type-county-year, we then average the number of young firm employees divided by total employees in each county-industry (from LEHD

QWI data), weighted by the industry's share of the equipment type in question. For example, if 2012 Durham, NC construction employment is 50 percent in young firms and logging employment is 25 percent in young firms, then we would measure $YoungFirmShare$ in the Durham, NC excavator market in 2012 as $0.5 \times 0.6 + 0.25 \times 0.4 = 0.4$—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 at a given point in time and certainly within an industry-county at a 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. If logging firms happen to be older, our test assumes log loaders will enjoy less young firm demand and hence, may turnover more slowly. Note, this allows us to identify the effects of young firm employment even with industry-county-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 9 About Here.]

Table 9 reports our findings. All regressions include fixed effects at the level of county-industry-year 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. In all specifications, we find that firms are more likely to replace equipment quickly when there are more young firms around.

The magnitudes appear plausible given estimation constraints. Note that the average probability of replacement at years three, four and five are just 0.01, 0.013, and 0.018—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 percents among users of a given machine type increases the probability of three, four, and five year replacement by 0.018, 0.020, 0.019. In each case, these more than double the mean frequency of 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.

References

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

Alchian, Armen A, and William R Allen, 1964, *University Economics* (Wadsworth: Belmont, CA).

Barrot, Jean-Noël, Erik Loualiche, Matthew C Plosser, and Julien Sauvagnat, 2018, Import competition and household debt .

Barrot, Jean-Noel, and Ramana Nanda, 2019, Can paying firms quicker affect aggregate employment?, *Journal of Finance* Forthcoming.

Benmelech, Efraim, and Nittai Bergman, 2011, Vintage capital and creditor protection, *Journal of Financial Economics* 99, 308–332.

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

Brown, Charles, and James L Medoff, 2003, Firm age and wages, *Journal of Labor Economics* 21, 677–697.

Davis, Morris A, Jonas DM Fisher, and Toni M Whited, 2014, Macroeconomic implications of agglomeration, *Econometrica* 82, 731–764.

Duranton, Gilles, and Diego Puga, 2004, Micro-foundations of urban agglomeration economies, in *Handbook of Regional and Urban Economics*, volume 4, 2063–2117 (Elsevier).

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

Eisfeldt, Andrea L, and Adriano A Rampini, 2006, Capital reallocation and liquidity, *Journal of Monetary Economics* 53, 369–399.

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

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

Ellison, Glenn, Edward L. Glaeser, and William R. Kerr, 2010, What causes industry agglomeration? evidence from coagglomeration patterns, *American Economic Review* 100, 1195–1213.

Ewens, Michael, Ramana Nanda, and Matthew Rhodes-Kropf, 2018, Cost of experimentation and the evolution of venture capital, *Journal of Financial Economics* 128, 422–442.

Gavazza, Alessandro, 2011a, Leasing and secondary markets: Theory and evidence from commercial aircraft, *Journal of Political Economy* 119, 325–377.

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

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

Gopal, Manasa, 2019, How collateral affects small business lending: The role of lender specialization .

Gopal, Manasa, and Philipp Schnabl, 2020, The rise of finance companies and fintech lenders in small business lending, *Working paper, New York University* .

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

Heckman, James J, 1979, Sample selection bias as a specification error, *Econometrica* 153–161.

Hsieh, Chang-Tai, and Peter J Klenow, 2009, Misallocation and manufacturing tfp in china and india, *The Quarterly journal of economics* 124, 1403–1448.

Hummels, David, 2007, Transportation costs and international trade in the second era of globalization, *Journal of Economic Perspectives* 21, 131–154.

Kerr, William R, and Scott Duke Kominers, 2015, Agglomerative forces and cluster shapes, *Review of Economics and Statistics* 97, 877–899.

Koch, Andrew, Marios A Panayides, and Shawn Thomas, 2020, Common ownership and competition in product markets, *Journal of Financial Economics* Forthcoming.

Marshall, Alfred, 1890, *Principles of Economics* (London, Mcmillan).

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

Ouimet, Paige, and Rebecca Zarutskie, 2014, Who works for startups? the relation between firm age, employee age, and growth, *Journal of financial Economics* 112, 386–407.

Petersen, Mitchell A, and Raghuram G Rajan, 1994, The benefits of lending relationships: Evidence from small business data, *Journal of Finance* 49, 3–37.

Puri, Manju, and Rebecca Zarutskie, 2012, On the lifecycle dynamics of venture-capital- and non-venture-capital-financed firms, *Journal of Finance* 67, 2247–2293.

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

Restuccia, Diego, and Richard Rogerson, 2017, The causes and costs of misallocation, *Journal of Economic Perspectives* 31, 151–74.

Figure 1. Sample UCC Filings

File Number: 20180102848F
Date Filed: 10/8/2018 12:08:00 PM
Elaine F. Marshall
NC Secretary of State

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)

1a. ORGANIZATION'S NAME
HOSS TREE WORKS & LOGGING, LLC

OR

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)

2a. ORGANIZATION'S NAME

OR

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)

3a. ORGANIZATION'S NAME
De Lage Landen Financial Services, Inc.

OR

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

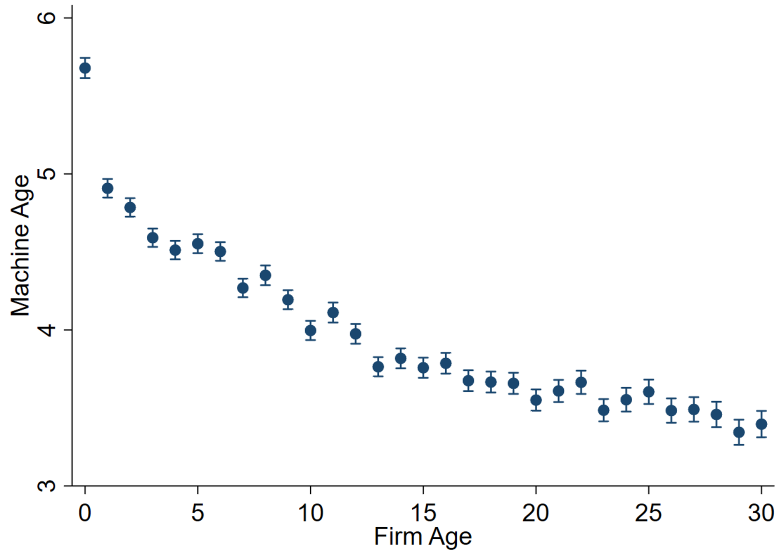
7. ALTERNATIVE DESIGNATION (if applicable): ☐ Lessee/Lessor ☐ Consignee/Consignor ☐ Seller/Buyer ☐ Bailee/Bailor ☐ Licensee/Licensor

8. OPTIONAL FILER REFERENCE DATA:
[153214210]

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

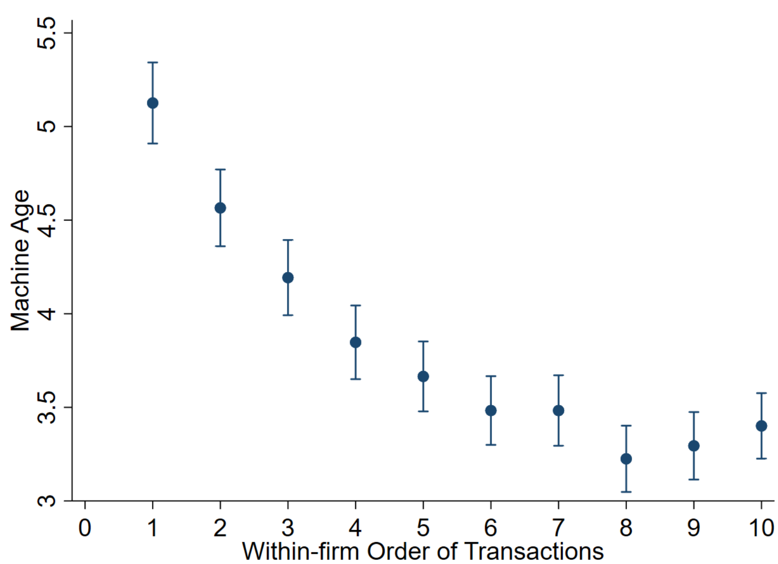
Notes. An example UCC filing from North Carolina for a Vermeer SC40TX stump cutter acquired by Hoss Tree Works and Logging in 2018.

Figure 2. Firm Age and Machine Age



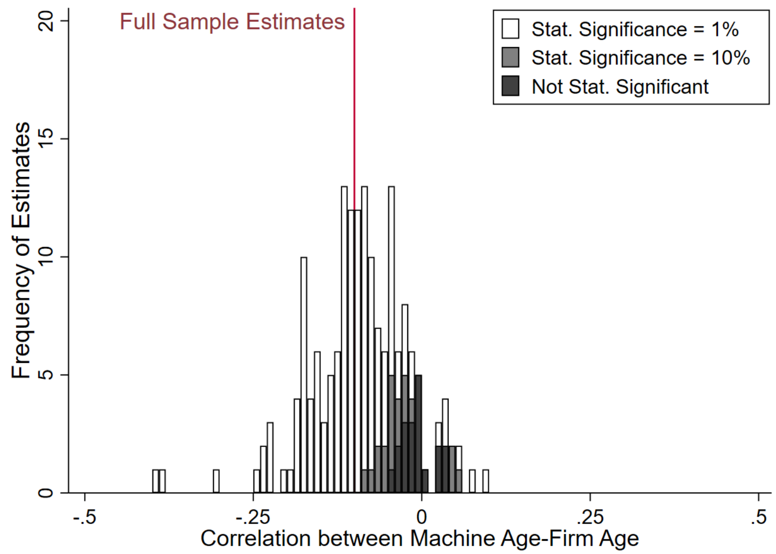
Notes. This graph plots the average age of machines purchased by firms across different age groups (1 to 30 years old), as well as the 95% confidence interval.

Figure 3. Trading Order and Machine Age

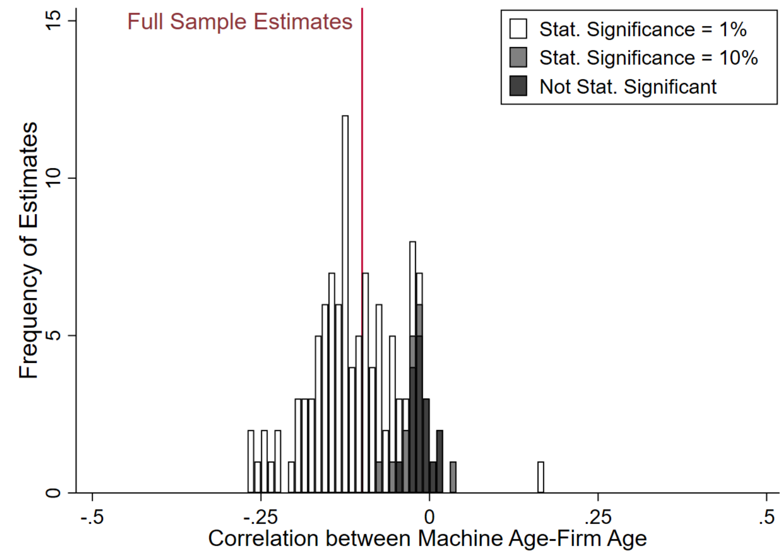


Notes. This graph plots the average age of machines purchased by firms across their own life cycles and the 95% confidence interval. The plot uses a group of firms that have at transactions in at least ten different years and follows the age of the machines they purchase over time.

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



(a) By-Industry Estimations



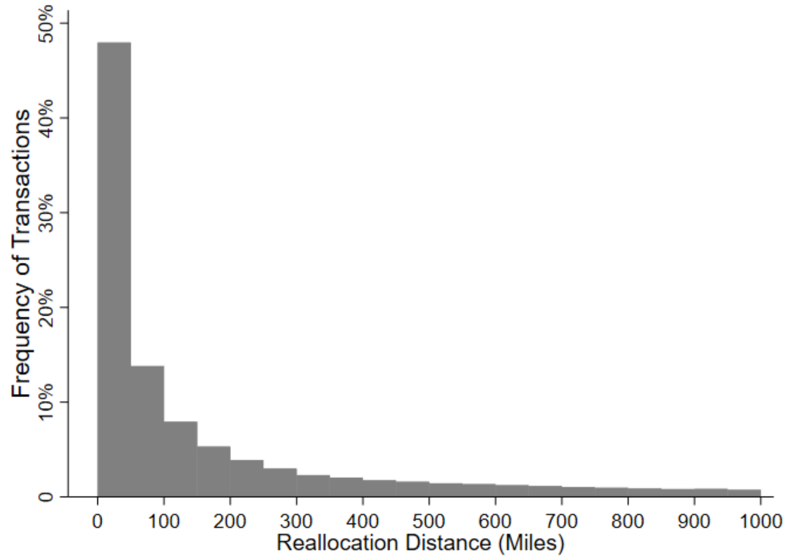
(b) By-Equipment Type Estimations

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

$$\log(1 + Machine\ Age)_i = \beta \times \log(1 + Firm\ Age)_i + \varepsilon_i.$$

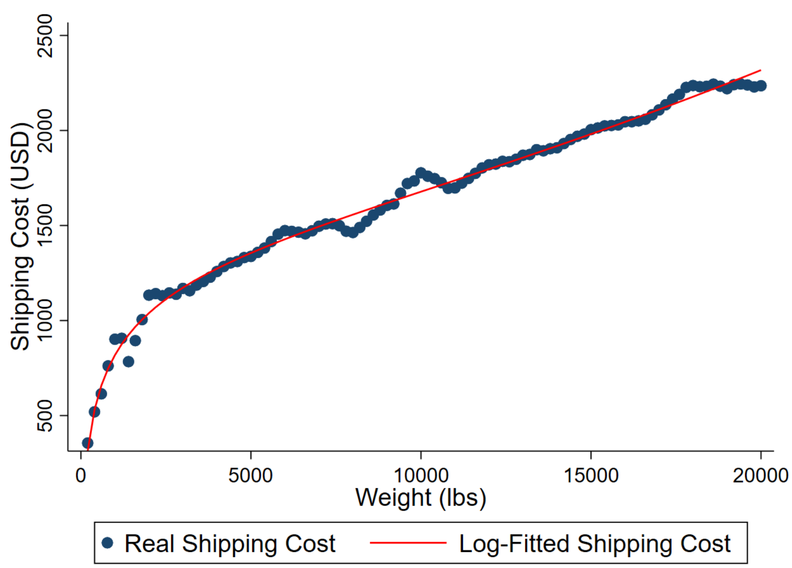
We include each 4-digit SIC industry for which we have at least 1,000 purchase observations in Panel (a) and each equipment type for which we have at least 1,000 purchase observations in Panel (b). The coefficients that are statistically significant at the 1% level are reported in white, those that are 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.

Figure 5. Histogram of Reallocation Distance



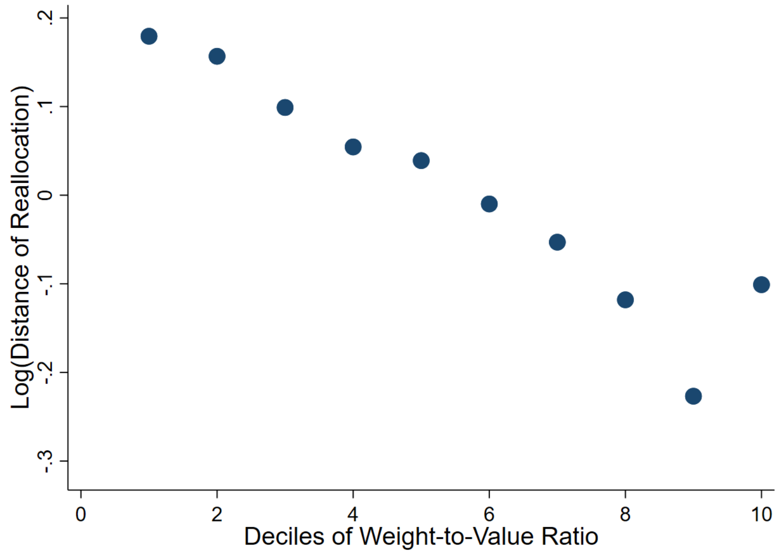
Notes. This figure presents the histogram of reallocation distances (in miles) for equipment transactions. The distances are calculated based on the addresses provided in the UCC filings.

Figure 6. Relation between Equipment Weight and Shipping Cost



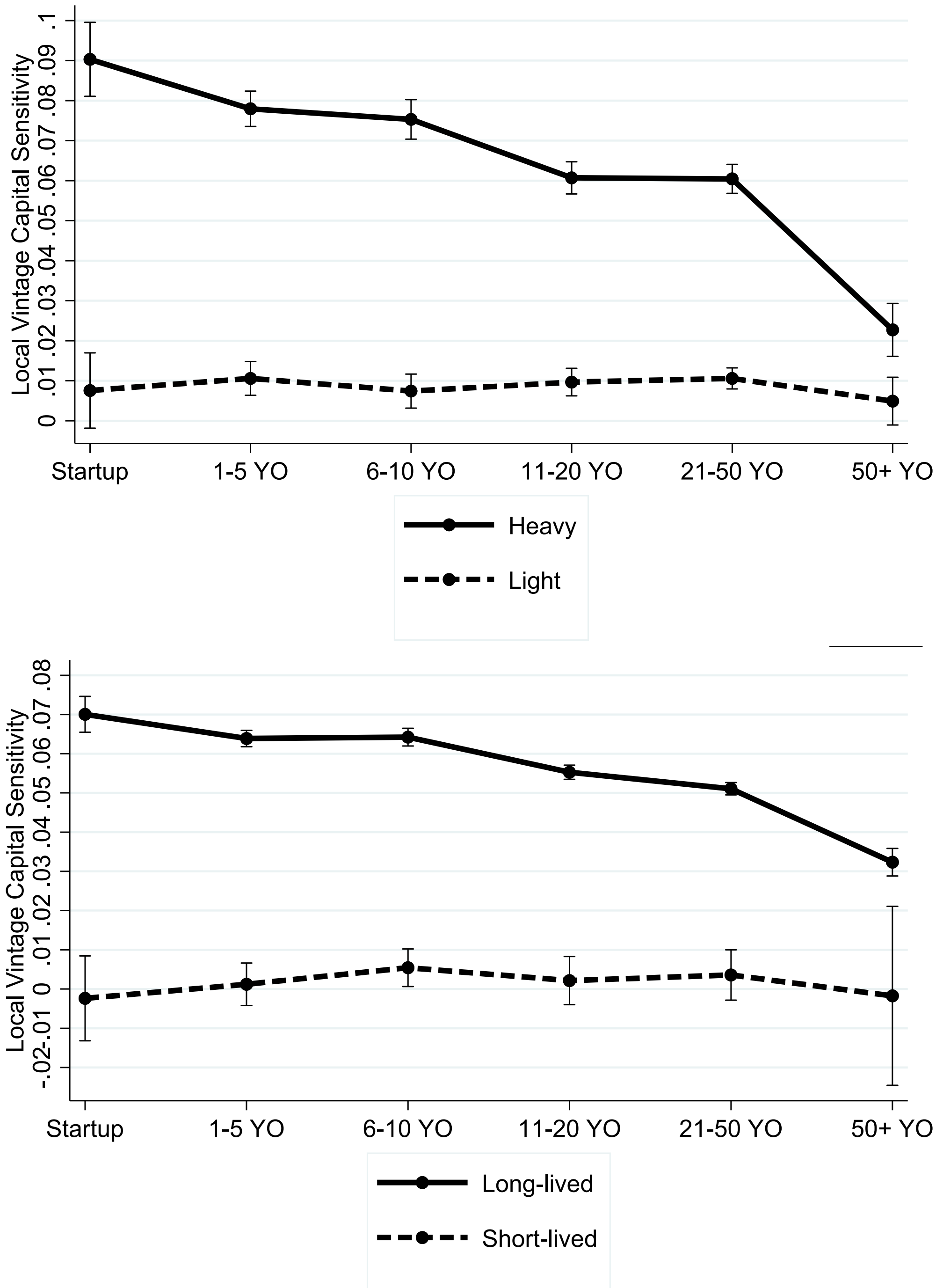
Notes. This figure plots the average shipping cost of equipment as a function of the total weight of the machine. Shipping costs are sampled through freight shipping broker uShip. For each weight, we sample the same set of 40 different routes of various distances (ranging from same county to cross country) and plot the average cost of the routes.

Figure 7. Weight-to-Value Ratio and Average Reallocation Distance



Notes. This figure presents a binned scattered plot of the weight-to-value ratio and average travel distance for different equipment types, conditional on the fixed effects from column (1) of Table 5 (excluding Machine Type fixed effects, since this subsumes the weight-to-value measure). Weight-to-value ratio is at the equipment-type level and is calculated as the 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



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 *LongLived* versus *ShortLived*) defined in Section 4.3. The reported coefficients are estimated from the following model

$$I(Bought) = \beta \times LocalVintageCapital + \delta_{FE} + \varepsilon,$$

using the fixed effects from column (1) of Table 6. We collect firms into six age groups that are reported in the horizontal axis. 95% confidence intervals are reported for each estimated point.

Table 1
Summary Statistics

Panel A: Firm and Machine Characteristics.

	Mean	Std.Dev	p25	Median	p75
Firm age (years)	22	24	7	16	29
Machine age (years)	4	7	0	1	5
Equipment value ($USD)	70,513	95,893	16,061	41,547	92,921

Panel B: Machine Transactions Tabulated by Buyer Industry.

	No of Obs	Percentage
Consumer NonDurables	171,417	11.19
Consumer Durables	22,664	1.48
Manufacturing	137,272	8.96
Oil, Gas, and Coal Extraction and Products	25,969	1.69
Chemicals and Allied Products	5,785	0.38
Business Equipment	5,621	0.37
Telephone and Television Transmission	2,003	0.13
Utilities	5,048	0.33
Wholesale, Retail	118,120	7.71
Healthcare, Medical Equipment, and Drugs	43,696	2.85
Finance	24,723	1.61
Mining	21,114	1.38
Construction	744,839	48.6
Transportation	58,183	3.8
Hotel	1,966	0.13
Business Service	33,919	2.21
Others	110,153	7.19
Total	1,532,492	100

Notes. Panel A provides descriptive statistics on the equipment purchases in the main sample. Firm age is the difference between the transaction year and the firm founding year. Machine Age is the difference between the transaction year 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. The table reports transactions based on buyer industries across the Fama-French 12 industries, where the "other" industry in Fama-French 12 is further decomposed to mining, construction, transportation, hotel, business service, and others.

Table 2
Firm Age and Machine Age in Equipment Transactions

	(1)	(2)	(3)	(4)
	Log(1+Machine Age)			
Log(1+Firm Age)	-0.103***	-0.105***	-0.081***	-0.088***
	[0.009]	[0.010]	[0.028]	[0.008]
Observations	1,532,492	1,532,492	1,532,492	1,532,492
R^2	0.131	0.261	0.533	0.589
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 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 logs. 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)
	Log(1+Machine Age)				Log(1+Model Age)
Log(1+Firm Age)	-0.103***	-0.112***	-0.110***	-0.108***	-0.005
	[0.010]	[0.007]	[0.009]	[0.010]	[0.004]
Log(1+Firm Age) x I(Shale Shock)	0.021***	0.022***			
	[0.007]	[0.008]			
Log(1+Firm Age) x Leasing			0.077***	0.081***	
			[0.011]	[0.005]	
Observations	705,086	705,086	2,078,608	2,078,608	861,529
R^2	0.226	0.343	0.162	0.281	0.159
County-Year FE	Y	Y	Y	Y	Y
Industry (SIC-3) FE	Y	Y	Y	Y	Y
Machine Type FE		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 is similar to that in Table 2. In columns (1) and (2), we interact the firm age variable with a dummy variable 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 relevant only after 2000. In columns (3) and (4), we use both the main sample of machine purchases and machine leases. We interact the firm age variable with a variable indicating lease transactions. Column (5) examines the relationship between model (technological) age and buyer firm age. *Model Age* is calculated as the number of years between the transaction and the introduction of the specific make and model. The analysis is performed on the transactions of 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.

Table 4
Nonincidental Sample Selection

Panel A: Machine Age and Sample Selection.

	(1)	(2)
	Selection into Sample	
New Machine	0.016***	0.006
	[0.006]	[0.005]
Log(1+Machine Age)	0.002	-0.003
	[0.003]	[0.004]
Observations	67,764	67,764
R^2	0.005	0.061
Year FE	Y	Y
Machine Type FE		Y

Panel B: Selection-free Analysis on Firm Age and Machine Age.

	(1)	(2)	(3)	(4)
	Log(1+Machine Age)			
	Full Sample (Table 2)		Machine Age $\geq$ 1 Only	
Log(1+Firm Age)	-0.103***	-0.105***	-0.090***	-0.089***
	[0.009]	[0.010]	[0.005]	[0.004]
Observations	1,532,492	1,532,492	922,343	922,343
R^2	0.131	0.261	-	-
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. Panel A documents the relationship between sample inclusion/exclusion and machine age. A missing sale is defined as a machine which did not reappear as a retail sale or lease within one year of being reported as part of an equipment dealer's wholesale floorplan financing. Panel B 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 used machines which are selection-free (columns (3) and (4)). The used machine analysis is estimated using truncated regressions. 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
Machine Age and Geographical Patterns of Equipment Reallocation

	(1)	(2)	(3)	(4)
	Log(Moving Distance)		I(Same-County)	
Log(1+Machine Age)	-0.090***		0.016***	
	[0.016]		[0.003]	
Number (order of transactions)		-0.081***		0.017***
		[0.020]		[0.003]
Observations	221,264	221,264	221,264	221,264
R^2	0.141	0.141	0.114	0.114
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

Notes. This table documents the relationship between the moving distance of a machine in a transaction and machine age. *Machine Age* is the number of years between the original manufacture date and the date of the transaction (columns (1) and (3)). As an alternative measure to capture machine age, we construct the order of transactions as the total number of prior transactions for the given machine (columns (2) and (4)). We capture moving distance in two ways—the logarithm of the distance between the buyer and the seller of a machine (in miles) in columns (1) and (2) and a dummy variable indicating whether the transaction was between two parties in the same county in columns (3) and (4). In all analyses we control for fixed effects at the level of year, industry, machine type, buyer county, and seller county. 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)
I(Bought)			Young Firms	
Local Vintage Capital	0.054***	0.053***	0.060***	-0.001
	[0.000]	[0.000]	[0.001]	[0.003]
Local Vintage Capital × Young Firm		0.005***		
		[0.001]		
Young Firm		-0.003***		
		[0.000]		
Local Vintage Capital × Heavy			0.009***	
			[0.002]	
Local Vintage Capital × Long Lived				0.065***
				[0.003]
Observations	1,918,053	1,918,053	347,022	347,022
R-squared	0.481	0.481	0.470	0.470
County-Year-Eqt Category FE	Y	Y	Y	Y
Machine Type FE	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 and all the other possible equipment types under the same equipment category. With the unit of observation being a potential machine purchase and the outcome of interest being whether or not a given machine was chosen, we then estimate the differential effect of vintage capital supply. $I(Bought) = 1$ for the realized machine purchases and 0 for equipment types not actually purchased. *Local Vintage Capital* is defined in Section 4.1 based on local transaction histories. The (logged) variable is standardized for interpretation. *Heavy* and *Long Lived* are based on machines types and defined in Section 4.3. *Young Firm* is an indicator for firms three years old or younger. Standard errors are clustered at the firm-year × equipment category level to capture the correlation across pseudo transactions and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Local Vintage Capital and Start-up Investment

Panel A: Local Vintage Capital and Young Firm Growth

	(1) Log(1+Total Investment)	(2) Log(1+Machine Types)	(3) Log(1+New Machines)
Local Vintage Capital_I	0.074***	0.060***	0.040***
	[0.014]	[0.011]	[0.008]
Observations	71,425	71,425	71,425
R-squared	0.229	0.235	0.203
Industry-Year FE	Y	Y	Y
County-Year FE	Y	Y	Y

Panel B: Heavy vs. Light Machines

	(1) Log(1+Total Investment)	(2) Log(1+Machine Types)	(3) Log(1+New Machines)
Local *Heavy* Capital_I	0.174***	0.136***	0.129***
	[0.044]	[0.037]	[0.033]
Local *Mid-weight* Capital_I	0.112***	0.090***	0.068***
	[0.032]	[0.026]	[0.020]
Local *Light* Capital_I	0.028	0.026*	0.000
	[0.018]	[0.016]	[0.014]
Observations	71,425	71,425	71,425
R^2	0.229	0.235	0.203
Industry-Year FE	Y	Y	Y
County-Year FE	Y	Y	Y
p-value of *Heavy* vs. *Light*	0.003	0.008	0.000

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

	(1) Log(1+Total Investment)	(2) Log(1+Machine Types)	(3) Log(1+New Machines)
Local *Long-Lived* Capital$_I$	0.087***	0.070***	0.047***
	[0.017]	[0.013]	[0.009]
Local *Short-Lived* Capital$_I$	-0.059	-0.044	-0.034
	[0.079]	[0.064]	[0.056]
Observations	71,425	71,425	71,425
R^2	0.229	0.235	0.203
Industry-Year FE	Y	Y	Y
County-Year FE	Y	Y	Y
p-value of *Long* vs. *Short*	0.096	0.105	0.168

Panel D: Young vs. Old Firms

	(1) Log(1+Total Investment)	(2) Log(1+Machine Types)	(3) Log(1+New Machines)
Local Vintage Capital$_I$ × Young Firm	0.013***	0.014***	0.003
	[0.005]	[0.005]	[0.004]
Young Firm	0.015**	0.014**	0.000
	[0.007]	[0.006]	[0.005]
Observations	372,657	372,657	372,657
R^2	0.396	0.398	0.379
County-Industry-Year FE	Y	Y	Y

Notes. This table examines the relationship between start-up investment activity and local vintage capital availability. All outcome variables measure investment during the period one to three years after the firm's first investment. *Total Investment* captures 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. Panels A through C include only investment by young firms (aged three years and younger). Panel D adds old firms (aged 10 years and older). *Local Vintage Capital$_I$* (Panels A and D) is an industry-level measure of available local capital, defined in Section 4.5. The (logged) variable is standardized for interpretation. *Local Heavy Capital$_I$* (Panel B) is the component of *Local Vintage Capital$_I$* made up of heavy (high weight-to-value) equipment, as defined in Section 4.3. Similarly for *Local Mid-weight Capital$_I$* and *Local Light Capital$_I$*. *Local Long-Lived Capital$_I$* (Panel C) is the component of *Local Vintage Capital$_I$* made up of equipment types with long market lives, as defined in Section 4.3. Similarly for *Local Short-Lived Capital$_I$*. The components of *Local Vintage Capital$_I$* in Panels B and C are scaled to make their coefficients comparable to the full measure in Panel A. *Young Firm* (Panel D) is an indicator for firms aged three years and younger. Standard errors are double clustered at industry and county level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Local Vintage Capital Availability and Start-up Employment

	(1)	(2)	(3)
	Log(Start-up Employment)		
Local Vintage Capital$_I$	0.185***		
	[0.063]		
Local *Heavy* Capital$_I$		0.467*	
		[0.263]	
Local *Mid-weight* Capital$_I$		0.219***	
		[0.046]	
Local *Light* Capital$_I$		0.059	
		[0.060]	
Local *Long-Lived* Capital$_I$			0.192**
			[0.072]
Local *Short-Lived* Capital$_I$			-0.049
			[0.066]
Observations	350,060	350,060	350,060
R^2	0.721	0.721	0.721
Industry-Year FE	Y	Y	Y
County-Year FE	Y	Y	Y
p-value of F-test		0.077	0.032

Notes. This table examines the relationship between start-up employment and local vintage capital availability. The analysis uses a sample at the county-industry-year level, where industry is 2-digit NAICS. *Start-up Employment* is the number of new jobs created by start-ups from t to $t+2$ as reported in the Census LEHD QWI data. *Local Vintage Capital$_I$* is an industry-level measure of available local capital, defined in Section 4.5. The (logged) variable is standardized for interpretation. *Local Heavy Capital$_I$* is the component of *Local Vintage Capital$_I$* made up of heavy (high weight-to-value) equipment, as defined in Section 4.3. Similarly for *Local Mid-weight Capital$_I$* and *Local Light Capital$_I$*. *Local Long-Lived Capital$_I$* is the component of *Local Vintage Capital$_I$* made up of equipment types with long market lives, as defined in Section 4.3. Similarly for *Local Short-Lived Capital$_I$*. The components of *Local Vintage Capital$_I$* are scaled to make their coefficients comparable to the full measure in column (1). Standard errors are double clustered at the industry and county level and are displayed in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Incumbent Capital Replacement

I(Replace)	(1) $\leq$ 3 Years	(2) $\leq$ 4 Years	(3) $\leq$ 5 Years
Young Firm Share	0.018**	0.020**	0.019*
	[0.007]	[0.009]	[0.011]
Observations	784,938	759,223	683,091
R-squared	0.145	0.157	0.163
County-Industry-Year FE	Y	Y	Y
Machine Type FE	Y	Y	Y

Notes. This table documents the relationship between the replacement period for a machine and the share of young firm employment in the same county that, based on industry and equipment type, are likely users of the machine. I(Replace) is an indicator equal to one if a given machine was sold (based on a subsequent transaction with the same serial number but matched to a different firm) and an identical machine type was acquired within 3, 4, or 5 years (for columns (1), (2), and (3), respectively). *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 (an example calculation is provided in Section 4.7). 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 cross-sectional measure for local liquidity based on Gilje, Loutskina, and Strahan (2016) that traces deposit shocks due to shale oil discoveries across the branch network of banks receiving large dollar inflows related to shale discoveries. We use data from 2000 to 2010 provided by Gilje, Loutskina, and Strahan (2016) capturing the timing and magnitude of major shale discoveries in seven states: Arkansas, Louisiana, North Dakota, Oklahoma, Pennsylvania, Texas, and West Virginia. For each bank with a branch in the county receiving a windfall, the liquidity measure allocates a proportional fraction of the shock, captured using the number of wells discovered, to active banks based on their fraction of total deposits held in a windfall county. This generates a bank-quarter level variable which we average at the county-quarter in non-windfall counties using the weight of those banks in the county. Formally, the variable *Shale Shock* is defined as

$$ShaleShock_{c,t} = \sum_{b \in B(c)} BankWeight_{b,c,t} \times \sum_{c \in C} BankWeight_{b,c,t} \times BankShare_{b,c,t} \times W_{c,t}. \quad (4)$$

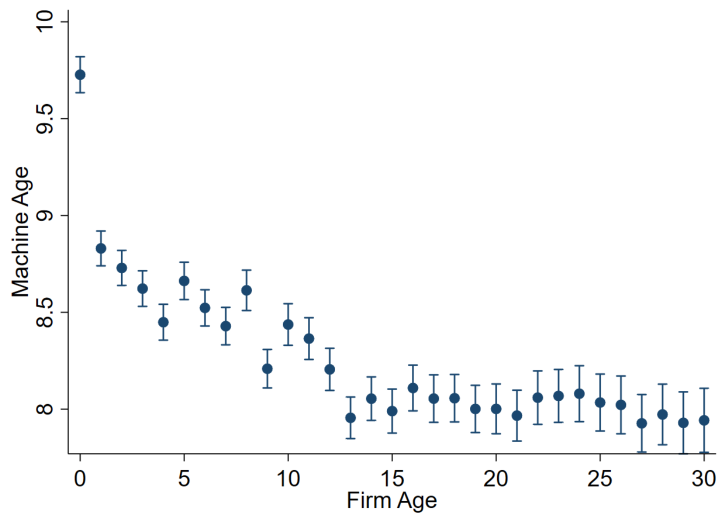
$W_{c,t}$ is the number of oil wells that have been discovered in county c by quarter t; $BankShare_{b,c,t}$ is the fraction of deposits that bank b holds in county c in quarter t as a fraction of total deposits in that county-quarter; and $BankWeight_{b,c,t}$ is the fraction of deposits that bank b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

A.2. Shipping Cost and Weight

Figure 6 in the paper plots the equipment shipping cost as a function of machine weight. To construct a data set of real world shipping costs, we use the equipment shipping broker website 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 all weights, ranging from same-county to roughly 3,000 miles. In Figure 6, we plot the average shipping cost across these 40 routes against weight and see a non-linear relation that fits a log-function well.

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 (1 to 30 years old), as well as the 95% confidence interval. The graph uses only transactions of used machines.

Table A1
Main Results with Inverse Hyperbolic Sine Transformation

	(1)	(2)	(3)	(4)
	IHS(Machine Age)			
IHS(Firm Age)	-0.098***	-0.100***	-0.080***	-0.084***
	[0.009]	[0.010]	[0.028]	[0.007]
Observations	1,532,492	1,532,492	1,532,492	1,532,492
R^2	0.131	0.264	0.537	0.600
Year x County 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 logarithm.

Table A2
Firm Age Distribution in UCC and Census LEHD QWI

Firm Age	Census Employment (%)	UCC Equipment Purchase (%)
0-1 YO	7.50	7.74
2-3 YO	7.61	7.20
4-5 YO	6.88	6.76
6+ YO	78.01	78.30

Notes. This table compares the firm age distribution of the UCC sample and the Census LEHD QWI sample.