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## CAPITAL SUPPLY SHOCKS AND INVESTMENT

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## Abstract

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JEL Classification: G31, G32, E22, E23, L26

Keywords: investment, Capital reallocation, Secondary markets, Smes, Supply chains, Covid-19



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# Capital Supply Shocks and Investment*

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**Abstract**

We examine how fixed capital supply shocks affect firms' investment. Using equipment transaction-level data, we find pandemic-driven production disruptions significantly altered capital reallocation patterns across firms. A surge in used capital trading activity softened the investment decline, as firms acquired used capital from distant and dissimilar counterparts. Younger firms were disproportionately affected even though they rarely purchase new capital: while in normal times older firms sell their capital to younger firms, following a supply shock, older firms compete for used capital, pricing out younger firms. Our evidence highlights the crucial role of secondary markets and distributive externalities for corporate investment.

*Keywords*: Investment, capital reallocation, secondary markets, SMEs, supply chain, COVID-19
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# 1 Introduction

Corporate investment is central to the macroeconomy and has implications for employment, productivity, and growth. While standard investment models typically include only a single vintage of capital, there is evidence that capital reallocation is a key dimension of investment [Eisfeldt and Rampini, 2006]. Some firms buy new capital from capital producers, but many others instead invest by purchasing used capital in *secondary markets* [Lanteri and Rampini, 2021, Lanteri, 2018]. Importantly, there are differences across firms: young firms tend to acquire used capital previously owned by older firms, consistent with cheaper used capital easing financial constraints [Ma et al., 2022, Eisfeldt and Rampini, 2007]. This suggests that the dynamics of secondary markets for used capital are central to understanding how shocks affect corporate investment in the cross-section of firms.

This paper studies a large-scale *capital supply shock*: the global production disruptions for new physical capital that occurred in 2021–22 during the COVID-19 pandemic. We exploit rich micro-data on transactions for new and used equipment to study the equilibrium effects of this shock on secondary markets, investment, and capital reallocation, with a specific focus on the differences across firms. We document a surge in secondary markets activity, as some firms switched to used capital to mitigate the shortage of new capital. In turn, this implies that younger firms were disproportionately affected even though they rarely purchase new capital: they invested relatively less after facing increased competition from older firms for used capital. Our evidence is consistent with models of heterogeneous firms with new and used capital and highlights the crucial role of secondary markets and distributive externalities for corporate investment [Lanteri and Rampini, 2021].

The shock we study is a large macroeconomic event that emanates from the COVID-19 pandemic. Several ensuing developments coalesced to significantly disrupt the production and shipment of equipment, required parts, and microchips. Labor shortages at manufacturing plants, shipping ports, and trucking companies, as well as an increase in the demand for consumer durable goods led to major supply chain disruptions. The head of Case New Holland, one of the world's largest equipment manufacturers, described the situation as "the worst supply chain [he's] seen in [his] career."[1] Supply chain disruptions have been ongoing since the onset of the pandemic, but were especially acute in late 2021. As some segments of the economy started to recover, there were many reports of fierce competition and sharp price increases for equipment during that period.

Our dataset consists of a sample of equipment transactions for U.S. firms, extracted from UCC filings. We observe the near universe of filings for agriculture, construction, logging, medical, office, and woodworking equipment plus forklifts and trucks. Our sample covers over 12 million unique assets securing ten million contracts originated between 1997 and March 2022. The contracts involve more than two million unique borrowers from every state and industry. For each transaction, we can observe the borrower and lender identity and location as well as detailed equipment information including the manufacturer, model, model year, and serial number. This granularity allows us to trace capital across time, location, and firms, providing an unprecedented glimpse into the dynamics of capital reallocation and investment after a large shock. For 5% of our sample, we can also observe prices. We match our transaction data with Dun & Bradstreet to study the effect of firm age, shown to be a key firm characteristic in prior investment work [Ma et al., 2022, Eisfeldt and Rampini, 2007, Hadlock and Pierce, 2010].

The first part of our paper documents a surge in secondary markets activity for used capital in the fall of 2021. Transactions were significantly more likely to include old equipment relative to normal times, consistent with firms switching to used capital when new capital becomes scarcer. Moreover, we find an increase in trading activity in secondary markets, with shorter times between consecutive sales of the same individual piece of equipment and greater geographic distance between successive buyers. There is also evidence of more trading of used equipment across buyers in different sectors, which is indicative of firms settling for second-best equipment for their needs or even harvesting equipment for electronics, chips, and parts.

[1] "'It's like Whack-a-Mole': tractors and trucks chief bemoans supply shortages" *Financial Times* July 7th 2021.

Together, this evidence is line with the idea that firms competed more aggressively for used capital during this time relative to normal times.

To sharpen identification, we exploit a labor strike at John Deere, the largest U.S. equipment manufacturer. John Deere is not only the largest agricultural equipment manufacturer in our sample, but also the second-largest construction equipment manufacturer (over 600,000 construction contracts in our sample). Over 10,000 production and warehouse workers walked off the job in the biggest private sector labor disruption in the United States since the General Motors strike in 2019. Thus the strike served as a meaningful disruption to multiple sectors of the economy. We run a Bartik estimation using pre-pandemic differences in John Deere's market share across equipment types to measure the heterogeneous exposure of *other manufacturers* to the strike. Importantly, we can now include location-by-time fixed effects to account for other concurrent shocks to investment demand or credit conditions. Intuitively, our tests compare used equipment price changes for manufacturers in markets where John Deere had a large market share (i.e., the supply shock is more consequential) to used equipment price changes for manufacturers in markets where John Deere had a small market share, while controlling for credit demand. We find bigger price increases in segments where John Deere had the largest market share, confirming that production disruptions had large effects on secondary market activity.

The second part of our paper studies the effects of the supply shock in the cross-section of firms. To guide the empirical analysis, we first present an illustrative framework of distributive effects in capital reallocation based on Lanteri and Rampini [2021]. There are overlapping generations of firms and two vintages of capital, new and old. Firms face financial frictions when purchasing capital and are endowed with heterogeneous levels of net worth. In equilibrium, the most financially constrained firms invest solely in old capital, whose cheaper price relaxes their financial constraints. The least financially constrained firms invest only in new capital, and firms in the intermediate group invest in a mix of both.

This illustrative framework generates two main empirical predictions for the equilibrium effects of a supply shock, modeled as a large increase in the cost of producing new capital. First, firms in the intermediate group experience the largest change in the age of their capital investment as they switch from new to used capital to dampen the shock. Second, the most financially constrained firms experience the largest drop in total investment, as they face additional competition for used capital. Interestingly, these spillovers effects imply that the most financially constrained firms are the ones most affected by supply shock, even if they do not purchase new capital. This is a direct consequence of the "distributive externalities" through secondary markets modeled in Dávila and Korinek [2018] and Lanteri and Rampini [2021].

We find evidence supporting the model's predictions. First, we identify a drastic change in the firm age–capital age gradient. In normal times, younger firms tend to invest in older capital, as shown in Ma et al. [2022]. After the shock, we see a spike in the age of capital for firms in the intermediate group of firm age. We also find that these firms actually increased investment in used capital relative to the oldest firms. This is in line with the first prediction of the model: intermediate firms are the ones that switch the most aggressively from new capital to used capital after the shock. Moreover, the youngest firms experienced the largest drop in total capital investment relative other firms. The economic magnitudes are again large: young firms' total investment volume dropped by 21 percentage points in relative terms. This evidence supports our second prediction and illustrates the relevance of distributive effects in explaining the cross-sectional response to this large macroeconomic shock. While the surge in secondary market activity dampened the shock for some firms, it priced out others.

We provide additional tests to support these inferences. First, we consider whether our findings are skewed by selection into the UCC data (we do not observe cash purchases). However, the young firms we focus on typically lack the cash to make such purchases. Additionally, our findings are similar if we add granular fixed effects controlling for various aspects of firm type, or if we weight our regressions based on the distribution of equipment type and location of wholesalers' inventory. Second, consistent with our main mechanism, we find that the effects of the shock on young firms are generally stronger in segments with low secondary market liquidity. Third, capital demand did not appear to be lower for young firms during these times: like other firms, younger firms travelled further and acquired capital from less similar firms than in normal times. Fourth, we find little evidence that a credit channel can explain our findings: the results do not vary with nonbank market share, and in placebo tests we do not find a similar capital reallocation during the 2008-09 financial crisis.

## 1.1 Related Literature

This paper relates to a large literature on capital reallocation across the business cycle. The closest papers to ours are Eisfeldt and Rampini [2007], Lanteri and Rampini [2021], Lanteri [2018]; see Eisfeldt and Shi [2018] for an extensive survey.[2] Compared to these works, we study the effects of a capital supply shock as opposed to productivity shocks. We also use rich transaction-level data that allow us to track equipment over location and time, compared to more aggregate or firm-level data typically used in empirical research. Our evidence provides additional support for these models in a different setting, highlighting the central role of capital reallocation and secondary market dynamics for the transmission of macroeconomic shocks.

We also contribute to research on the drivers of small business investment. The market for equipment includes many small and private firms [Murfin and Pratt, 2019, Gopal and Schnabl, 2020, Darmouni and Sutherland, 2021], and these firms often invest in the form of used capital [Ma et al., 2022]. Compared to these prior works, we provide new evidence on the dynamics of secondary markets and capital reallocation following a large-scale production shock. We also provide some of the first micro-evidence in support of distributive externalities highlighted in a growing macroeconomic theory literature [Lanteri and Rampini, 2021, Dávila and Korinek, 2018]. We show the empirical relevance of this view of pecuniary externalities

[2] Important works that study different facets of capital reallocation include Eisfeldt [2004], Eisfeldt and Rampini [2006], Li and Whited [2015], Eberly and Wang [2009], Gavazza [2011], Midrigan and Xu [2014], Ottonello [2021], Giroud and Mueller [2015], Cui [2022], Fuchs et al. [2016], Gopinath et al. [2017], Kehrig and Vincent [2017], Wright et al. [2018].

in the context of a large recent macroeconomic shock.

# 2 Background and Data

## 2.1 The 2021-22 Production Disruptions

The supply chain shock we study emanated from the COVID-19 pandemic. Several developments coalesced to significantly disrupt the production and shipment of equipment, necessary parts, and microchips. First, production worker illnesses and stay-at-home orders led to labor shortages that made it more difficult for manufacturers to meet demand. Second, similar labor shortages at major ports and among rail and trucking workers caused extended wait times. Delays in processing and moving cargo in turn caused a shortage in available shipping containers that exacerbated the problems. Third, over recent decades, suppliers embraced a "lean manufacturing" model focused on matching production to demand. While such an approach promotes efficiency and productivity, it does so at the cost of slack that helps suppliers manage labor disruptions, shipping delays, and demand shocks. Meanwhile, stay-at-home orders, sharp increases in remote meetings and learning, and government relief programs led to a demand surge for microchips, a key component in computers, automobiles, and equipment with electronic interfaces.

As a result, equipment manufacturers faced significant shortages of labor and key components including steel, plastics, rubber, and computer chips. The head of Case New Holland, one of the world's largest equipment manufacturers, described the situation as *"the worst supply chain I've seen in my career... Dealers had to tell customers they had to wait, sometimes as long as 12 months, to get a new machine. Firms immediately turned to late-model machinery to meet their needs, but rapidly it began to disappear."* Supply chain disruptions have been ongoing since the onset of the pandemic but were especially acute in late 2021. Our analysis examines multiple periods, including one spanning a specific labor strike affecting John Deere, the manufacturer in our sample providing the most equipment. Most of our tests use November 2021 as a cutoff because by that date the equipment shortage was indisputably pervasive,[3] although our results are robust to using other windows.

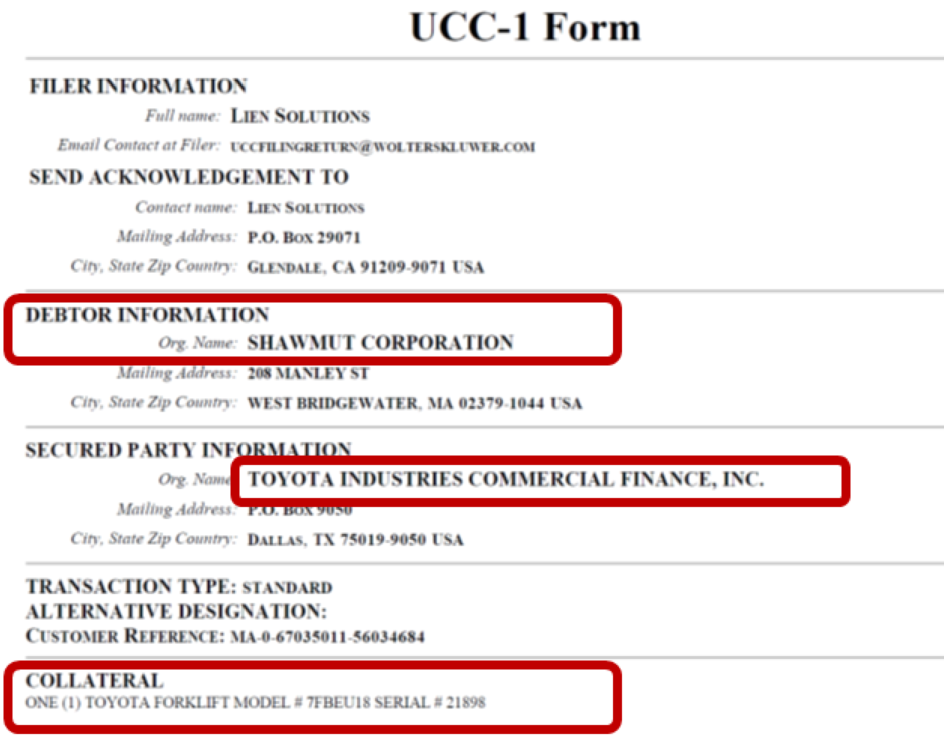
## 2.2 Data

We obtain a sample of public liens on business property (excluding real estate), also known as "UCC filings" or "UCC-1 filings." For secured loans in the United States, lenders make UCC filings with the Secretary of State in the borrower's state to legally establish their claim to the collateral pledged by the borrower. Filings typically identify the borrower, lender, filing date, and collateral information. For example, UCC filings detail the manufacturer, model, model year, and serial number to ensure correct identification of the asset in the event of default or dispute with another lender. Given these filings protect the lender's claim to collateral in the event of default and are inexpensive (typically $25 or less to file), UCC filing datasets provide comprehensive coverage of secured commercial lending in the United States. Figure 1 provides an example UCC filing.

Our UCC filing dataset comes from Randall-Reilly, a data vendor focused on the equipment finance sector. Their EDA dataset compiles UCC filings dating back to the 1990s, covering agriculture, construction, office, lift trucks, logging, machine tools, medical, trucking, and woodworking equipment. From each UCC filing it extracts the borrower and lender identity and location as well as collateral information. It cleans this collateral information by standardizing equipment manufacturer and model information and assigning assets to one of 497 equipment codes. It also supplements UCC filing information with additional borrower information (including a Dun & Bradstreet (DNB) number, which allows us to measure firm age). Five percent of UCC filings contain an equipment value; in many of the remaining cases EDA appends an equipment value based on its database of list prices, auction values, trade publications, and survey information.

Randall-Reilly sells versions of its EDA dataset as a marketing and market intelligence

[3] See for example "What led to the machinery shortage of 2021 and what to expect for 2022," November 19, 2021, Agriculture.com.



UCC-1 Form

FILER INFORMATION

Full name: LIEN SOLUTIONS

Email Contact at Filer: UCCFILINGRETURN@WOLTERSKLUWER.COM

SEND ACKNOWLEDGEMENT TO

Contact name: LIEN SOLUTIONS

Mailing Address: P.O. BOX 29071

City, State Zip Country: GLENDALE, CA 91209-9071 USA

DEBTOR INFORMATION

Org. Name: SHAWMUT CORPORATION

Mailing Address: 208 MANLEY ST

City, State Zip Country: WEST BRIDGEWATER, MA 02379-1044 USA

SECURED PARTY INFORMATION

Org. Name: TOYOTA INDUSTRIES COMMERCIAL FINANCE, INC.

Mailing Address: P.O. BOX 9050

City, State Zip Country: DALLAS, TX 75019-9050 USA

TRANSACTION TYPE: STANDARD

ALTERNATIVE DESIGNATION:

CUSTOMER REFERENCE: MA-0-67035011-56034684

COLLATERAL

ONE (1) TOYOTA FORKLIFT MODEL # 7FBEU18 SERIAL # 21898

Figure 1: Example of UCC Filing

tool to over 4,400 equipment manufacturers and lenders. UCC filing data similar to that examined in our study (from EDA or other vendors) is used in Edgerton (2012); Thakor (2018); Murfin and Pratt (2019); Gopal (2021); Ma, Murfin, and Pratt (2022); and Gopal and Schnabl (2022), among others. Because the dataset does not contain loan sizes, just equipment values for some observations and estimated values for most others, we focus on the number of secured transactions, which has been shown to be highly correlated with loan volume in prior work. For example, Gopal and Schnabl [2020] show that there is strong empirical support for this assumption using both Community Reinvestment Act (CRA) data and EDA data. The correlation between the volume of lending and the loan count at the county-year level is very high: 90% for CRA data and 97% for EDA data.

Following Ma et al. [2022], we eliminate UCC filings where the debtor is a wholesaler, equipment seller, rental or leasing company, auctioneer, or government such that our tests focus on the end users of equipment. Our sample covers over 12 million assets securing ten million contracts originated between 1997 and March 2022. The contracts involve more

| | p25 | Median | p75 | Av. | N |
|---|---|---|---|---|---|
| Eq. Age (Y) | 0 | 1 | 6 | 4.77 | 12M |
| % New Eq. | - | - | - | 60.5 | 18M |
| Used Eq. Estimated Value (USD) | 12,482 | 31,772 | 74,250 | 55,422 | 7M |
| New Eq. Estimated Value (USD) | 9,799 | 27,548 | 76,715 | 64,282 | 10M |
| Firm Age (Y) | 4 | 13 | 29 | 21.0 | 16M |

Table 1: Summary Statistics

**Notes:** This table present summary statistics for our sample of contracts. We eliminate UCC filings where the debtor is a wholesaler, equipment seller, rental or leasing company, auctioneer, or government. The time period includes contracts originated between 1997 and March 2022. The estimated equipment values are provided by the EDA. Firm age is from Dun & Bradstreet.

than two million unique borrowers from every state and industry. Table 1 presents summary statistics. The average (median) equipment age is 4.77 (one) year old. Sixty-one percent of contracts are secured by new equipment. The average (median) estimated value of used equipment is $55k ($32k), and for new equipment is $64k ($27k) (newer assets commonly include less expensive categories such as computers).

Our primary measure of firm heterogeneity is age, following classical work on capital reallocation [Eisfeldt and Rampini, 2007, Ma et al., 2022, Lanteri and Rampini, 2021]. A great advantage of the UCC data is that it covers a significant number of small private firms whose behavior is difficult to study with other datasets. One caveat is that the information we can observe about each firm is limited. In particular, we have no accounting or balance sheet information. We follow existing literature and use firm age from DNB as a proxy for financial constraints. While this measure is imperfect, previous work has shown empirically that the effect of age is consistent with predictions of models of financial constraints in which younger firms are relatively more constrained. It is also widely observable in our sample, as firm age is available for over 80% of the observations.[4]

Finally, it is worth repeating that another limitation of our sample is that by construction it is restricted to equipment with a lien. It thus excludes transactions in which the buyer fully paid in cash. Our sample is thus tilted toward smaller firms that are more likely to use secured

[4]For instance, Hadlock and Pierce [2010] have argued that age is a valid proxy for financial constraints.

financing or leases to acquire fixed assets. Section 5.4 provides additional tests to verify that our main results are not driven by selection into the UCC dataset.

# 3 Secondary Market Activity

In this section, we provide micro-evidence on changes in secondary market activity in the fall of 2021. The next section will study differential effects on investment in the cross-section of firms.

## 3.1 Higher Share of Transactions for Old Capital

We first study whether transactions are more likely to include used capital as opposed to new capital following the production shock. We estimate the following regression specification:

$$NewCapital_{i,e,t} = \mathbf{1}\{\text{Post Nov 21 Crunch}\} + \nu^c + u^{e,t} + \zeta^m + \varepsilon^{i,e,t}$$

The dependent variable is either an indicator for the equipment being new or the log equipment age (in years). The variable of interest is an indicator for the period beginning in November 2021 and ending in March 2022 (the last month of our sample).[5] We include county fixed effects to control for persistent differences across local markets as well as equipment code-by-calendar month fixed effects. These are important to control for seasonality, which can be an important driver for investment demand. The most stringent specifications also include manufacturer-model fixed effects to estimate the change *within a particular equipment model.* The sample includes all contracts from January 2019 to March 2022. We cluster our standard errors by month-year; clustering instead by equipment code does not affect our inferences.

Table 2 presents the results. Column 1 shows that during the supply chain disruption period, transactions are significantly less likely to include new equipment. Column 2 confirms this result by showing that the average equipment age is also higher. The results are even

[5] To the extent that the timing of the shock was diffuse, this would likely attenuate our results toward zero.

| | (1) New | (2) Log (1+Equipment Age) | (3) New | (4) Log (1+Equipment Age) |
|---|---|---|---|---|
| Post Nov 21 Crunch | -0.033*** | 0.053*** | -0.077*** | 0.163*** |
| | [-5.76] | [3.62] | [-9.02] | [6.68] |
| Observations | 2254842 | 1573826 | 2211339 | 1548352 |
| Adjusted $R^2$ | 0.069 | 0.058 | 0.532 | 0.694 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: New vs. Used Capital Transactions

**Notes:** This table models equipment age as a function of time. The unit of observation is a transaction for a particular piece of equipment. The dependent variable in Columns 1 and 3 is an indicator variable equal to 1 if the equipment is new, and 0 if used; in Columns 2 and 4 the dependent variable is the log of equipment age. Columns 1 and 2 include county and equipment code $\times$ calendar month fixed effects, while Columns 3 and 4 add manufacturer-model fixed effects. The sample includes all contracts from January 2019 to March 2022. Standard errors are clustered by month-year.

stronger in Columns 3 and 4 that look at changes within the same equipment model. This evidence is consistent with firms switching to used capital when new capital becomes scarcer.

## 3.2 Trading Activity for Old Capital

To provide more direct evidence of an increase in demand for used capital, we leverage the fact that we can track individual pieces of equipment over time and location using granular data that allow us to develop a measure of trading activity in secondary markets that would be difficult to construct using more aggregated data.

In particular, we aim to capture the idea that firms competed more aggressively for used capital during the supply chain disruption relative to normal times. The following quote from November 2021 illustrates this competition:

> There was this John Deere tractor up for sale at the auction in Keymar, **Maryland**. It was **old** – built in 1998 – but lightly used, having clocked fewer than 1,000 hours, and in pristine condition. The bidding started at $100,000 and quickly shot up to a final sale price of $170,000. **That's $25,000 over the previous record for that specific model.** (Brand-new versions start at $205,000.) The buyer was

> so desperate to get his hands on a tractor that **he drove all the way in from Illinois** to bid on this one. When he won, he loaded it onto a trailer hitched to his truck and hauled it 12 hours back home.[6]

This suggests that used equipment would sell faster and across more-distant locations during the supply chain disruption. We run the following regression to test this prediction:

$$TradingActivity_{e,t} = \mathbf{1}\{\text{Year 2021}\} + \xi^e + a^{e,t} + \nu^c + u^t + \varepsilon^{e,t}$$

The dependent variable measures different aspects of trading activity: the time between the last two sales, and geographic distance measures between the last two buyers. Our variable of interest is an indicator for 2021 and 2022: in this regression we use a yearly indicator over a monthly indicator as trading activity is difficult to measure precisely at a high-frequency. The sample includes all equipment that transacted at least twice. This allows us to include serial number fixed effects, to identify the change in trading intensity in this period keeping the specific piece of equipment and its specification (manufacturer, model, vintage, and features) fixed. We also include dummies for each yearly equipment age level as well as county and calendar month fixed effects, to account for the persistent effects of local markets or seasonality.

Table 3 presents the results. We find evidence of an increase in trading market intensity after the shock. Columns 1 and 2 show that the time between sales significantly reduced during this episode relative to normal times. This suggests that used equipment took less time than normal to find a buyer, consistent with heightened demand. Concretely, it is plausible that running down inventories of used equipment by dealers was an important driver of the increase in used capital investment. Indeed, many dealers reported having sold their entire stock during 2021.[7] This reduction in time between sales in interesting given that firms were likely reluctant to part with their equipment during this time, pushing in the other direction by reducing the

[6] "Wild bidding wars erupt at used-tractor auctions across the U.S." Bloomberg, Nov. 13, 2021.

[7] *"Dealers had to tell customers they had to wait, sometimes as long as 12 months, to get a new machine. Firms immediately turned to late-model machinery to meet their needs, but rapidly it began to disappear"* What led to the machinery shortage of 2021 and what to expect for 2022, Nov. 19, 2021, Agriculture.com.

| | (1) Log Time Since Last Contract | (2) Log Time Since Last Contract | (3) Log Distance | (4) Log Distance | (5) Same County | (6) Same County |
|---|---|---|---|---|---|---|
| Year 2021/2 | -0.148*** | | 0.051** | | -0.018*** | |
| | [-11.99] | | [2.33] | | [-3.86] | |
| Year 2021 | | -0.135*** | | 0.067*** | | -0.019*** |
| | | [-10.35] | | [2.90] | | [-3.88] |
| Observations | 288517 | 288517 | 329548 | 329548 | 345240 | 345240 |
| Adjusted $R^2$ | 0.443 | 0.443 | 0.445 | 0.445 | 0.324 | 0.324 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Trading Activity in Used Capital

**Notes:** This table models secondary market activity as a function of time. The unit of observation is a transaction for a particular piece of equipment. The dependent variable in Columns 1 and 2 is the log of days between the last two transactions for that equipment; in Columns 3 and 4 it is the log number of miles between the counties of the last two users of that equipment; Columns 5 and 6 use an indicator variable for the same county instead of log distance. All specifications include equipment serial number, county and calendar month fixed effects, as well indicators for each year of equipment age. The sample includes all equipment that transacted at least twice. Standard errors are clustered by serial number.

number of assets for sale. Nevertheless, our evidence suggests that the increase in demand was large enough to empirically dominate.

We also find greater geographic distance between consecutive buyers. Columns 3–6 show that consecutive users of equipment were further apart. The miles between the past and current user increase by 5%–6% and they were 2 percentage points less likely to be located in the same county. For context, the past and current users are in the same county about 20% of the time. These distance findings are notable because equipment types are heavy and therefore costly to transport.

We also find evidence for more trading of used equipment across buyers in different sectors. Table 4 shows the results for similar specifications as above, but for measures of sectoral similarity between the last two buyers of a specific piece of equipment. Columns 1 and 2 show that in 2021, there was a lower probability that last two buyers were in same industry. Columns 3–6 show a similar pattern for indicators of whether the last two buyers shared the same modal equipment type. To illustrate this finding, consider a piece of equipment that was previously operated by a firm that predominantly invests in a certain type of truck. In 2021, this equipment was more likely to subsequently to be used by a firm that does *not* predominantly invest in the same type of truck, relative to previous years. One interpretation

| | (1) Same SIC2 | (2) Same SIC2 | (3) Same Modal Eq. Code | (4) Same Modal Eq. Code | (5) Same Modal Eq. Family | (6) Same Modal Eq. Family |
|---|---|---|---|---|---|---|
| Year 2021/2 | -0.017*** | | -0.012** | | -0.020*** | |
| | [-2.92] | | [-2.10] | | [-6.07] | |
| Year 2021 | | -0.022*** | | -0.009 | | -0.018*** |
| | | [-3.56] | | [-1.48] | | [-5.13] |
| Observations | 345240 | 345240 | 345240 | 345240 | 345240 | 345240 |
| Adjusted $R^2$ | 0.275 | 0.275 | 0.352 | 0.352 | 0.459 | 0.459 |

$t$ statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Trading Activity in Used Capital: Across Sectors and Main Equipment

**Notes:** This table models secondary market activity as a function of time. The unit of observation is a transaction for a particular piece of equipment. The dependent variable in Columns 1-2 is an indicator equal to 1 if the last two users of that equipment are in the same two-digit SIC code; in Columns 3-4 it is an indicator equal to 1 if the last two users of that equipment share the same model equipment code (defined over their previous transactions); Columns 5-6 use equipment family instead of equipment code. All specifications include serial number, county and calendar month fixed effects, as well equipment age (in year) indicators. The sample includes all equipment that transacted at least twice. Standard errors are clustered by month-year.

is that buyers are more likely to purchase capital that is further from their ideal type, revealing an additional willingness to substitute after the shock. A more extreme possibility is that some firms acquired different equipment to access parts that were otherwise difficult to acquire. In other words, the firm acquired the asset intending to harvest it for parts or re-purpose it in some way.[8]

## 3.3 Isolating a Supply Shock: John Deere Strike

The evidence from the previous section is consistent with the 2021 production disruptions leading to a demand shock for used capital. Nevertheless, from an identification perspective, the previous empirical analysis relied on *time series variation*, comparing the recent months to normal times. A concern is that the supply shock was not the only aggregate shock to hit the economy during this time, and that equipment markets might have fluctuated for different reasons during this episode. For example, there might have been a change in investment demand or credit conditions due to the macroeconomic recovery or government interventions to alleviate the effects of the pandemic.

[8]For example, firms report acquiring washing machines for the sole purpose of stripping out their electronics: "The chip shortage is so bad companies are ripping them out of washing machines", Protocol April 20, 2022.

In this section, to address these concerns, we exploit a labor strike at John Deere to isolate additional *cross-sectional variation* in the exposure to a supply shock. John Deere is the largest U.S. equipment manufacturer, specializing in agricultural and construction equipment. Between October and November 2021, about 10,000 production and warehouse employees went on strike across 14 U.S. plants. This was the largest strike ever at John Deere and the largest private sector strike in the United States since the 2019 General Motors strike. The strike raised many concerns among end users of capital, as it happened in a period in which global production disruptions were already in full force.[9] Because John Deere is the largest agricultural equipment manufacturer in the United States and the second-largest construction equipment manufacturer (next to Catepillar, Inc.), the strike served as a major disruption that affected multiple sectors in all parts of the country. The strike led to a severe production backlog. Investment bank William Blair & Company estimated that the strike reduced John Deere's output by 10% to 15% for 2021Q4 and 2022Q1. Consistent with this, we observe a distinct decline in new equipment from John Deere compared to its competitors following the strike (see Table IA.1 in the Internet Appendix). This had a negative effect on an already tight secondary market: *"With the four-week-old strike at Deere factories exacerbating an already acute shortage of new tractors, the used market is the only place for many desperate farmers to turn."*[10]

Our identification strategy in this section exploits the heterogeneous exposure of *other manufacturers* to the strike. Intuitively, market segments in which John Deere has a larger presence are more likely to experience supply shortages and see firms turn to other manufacturers relative to other market segments. Specifically, we run a Bartik-like specification. We exploit 2019 pre-pandemic differences in John Deere's market share across equipment types. To illustrate, in 2019 John Deere had over a 50% market share in the crawler dozers market versus a 12% share in the skid steer loaders market. In the sample of equipment transactions not involving John Deere equipment, we regress the value of used equipment on a Strike $\times$

[9] "Farmers and John Deere suppliers worry about strike's impact." Associated Press. October 17, 2021.
[10] "Deere's Strike Is Over, but Order Backlog, Higher Costs Remain," Wall Street Journal, Nov. 22, 2021.

2019 Deere Market Share interaction, where the strike period is defined as December 2021 through January 2022 (the strike ran from October to November 2021, and given production and shipping time, it typically takes a month or two for equipment to appear in a UCC filing). Importantly, we can include granular time fixed effects (in addition to others) to account for other concurrent shocks to investment demand or credit conditions because we now have a supply shock that varies in the cross-section of market segments.

Table 5 presents the results. Columns 1 and 2 use the smaller subsample for which actual prices are available, while Columns 3 and 4 also include estimated values with tighter fixed effects. We find that used equipment experienced larger price increases in segments where John Deere had the largest market share. The effects are sizeable: the estimate of Column 2 implies that a one standard deviation increase in John Deere's 2019 market share ( $\approx 0.25$) increases other manufacturers' prices by 25% during the strike. The lower magnitudes in Columns 3 and 4 presumably reflect that estimated values are often stale, attenuating the coefficient toward zero. These results are consistent with our earlier evidence on secondary markets, confirming that production disruptions were a key driver of the surge of secondary market activity in the fall of 2021.

# 4 Distributive Effects: Illustrative Model

The next sections study the effects of the supply shock in the cross-section of firms. To guide the empirical analysis, we first present an illustrative framework to generate our main predictions. The following section then tests these predictions using our micro-data. Nevertheless, a full theoretical analysis of capital supply shocks is beyond the scope of this paper.

## 4.1 A Simple Model of Capital Reallocation

We present the most parsimonious setting that can generate the cross-sectional effects we are interested in, and follow the capital reallocation model of Lanteri and Rampini [2021]. There

| | (1) Log Price-Used | (2) Log Price-Used | (3) Log Price-Used | (4) Log Price-Used |
|---|---|---|---|---|
| Strike x Deere Share 2019 | 0.868** | 1.006*** | 0.126** | 0.112** |
| | [2.51] | [3.21] | [2.67] | [2.72] |
| Deere Share 2019 | 0.511 | 1.857* | | |
| | [0.60] | [1.94] | | |
| Log (1+ Equipment Age) | -0.597*** | -0.646*** | -0.164*** | -0.164*** |
| | [-6.32] | [-10.24] | [-5.14] | [-5.13] |
| Observations | 33666 | 33666 | 1718256 | 1718146 |
| Adjusted $R^2$ | 0.222 | 0.392 | 0.959 | 0.959 |

*t* statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: John Deere Strike: Price of Used Capital for Other Manufacturers

**Notes:** This table studies equipment prices as a function of time and John Deere's market share in the equipment market. Strike is an indicator variable for December 2021 to January 2022. Deere Share 2019 is the share of contracts in that equipment code that involve equipment manufactured by John Deere, measured in 2019. The unit of observation is a transaction for a particular piece of equipment. Fixed effects in each column: (1) month × year, and state; (2) month × year, state, and equipment family; (3) month × year, county, and manufacturer × model; (4) state × month × year, and manufacturer × model. The sample excludes equipment manufactured by John Deere itself. Columns 1 and 2 include only used equipment for which the actual price is reported, whereas columns 3 and 4 include used equipment with actual prices or values estimated by the data vendor. Standard errors are clustered by month-year.

are overlapping generations of firms that live for two periods. They buy capital in first period and produce output in second period. All firms are owned by a household with discount rate $\beta$. Capital is productive for only two periods, which creates two vintages of capital. New capital $k^N$ has two remaining years of useful life, while used capital $k^O$ has only one year left. The two are imperfect substitutes in producing output.

There are financial frictions in investment. Firms are born with heterogeneous net worth $w$. To finance capital investment, firms can borrow at rate $\beta^{-1}$ subject to a collateral constraint. They can borrow only a fraction $\theta \in [0, 1)$ of the value of the capital, assumed to be constant across vintages for simplicity. If additional funds are needed, firms can raise additional external financing subject to a convex cost function $\phi$.

Output can be used to pay dividends to households or produce new capital. We model the supply shock in the following way. The initial cost of producing new capital is normalized to one unit of consumption good. After the shock, this cost increases to $1 + \Delta$. For simplicity, we assume the economy was initially in a stationary equilibrium and that the shock was not anticipated.[11]

## 4.2 Capital Choices Across Firms

The equilibrium characterization prior to the shock is intuitive and described in more detail in Lanteri and Rampini [2021]. The choice of capital investment in the cross-section of firms is illustrated in the top half of Figure 2. Starting from new capital investment in the top left, we see that only firms with sufficient net worth invest in new capital. Intuitively, new capital has a lower user cost but is more expensive: it requires a higher down payment. More financially constrained firms thus prefer to invest in cheaper used capital, as can be seem in the top right panel. Firms with enough net worth are unconstrained and invest in the first-best level of capital, using new capital only. The set of firms with intermediate net worth is particularly interesting: these are firms that in equilibrium invest in both new and used capital. The mix is tilted more toward new capital the higher their net worth.

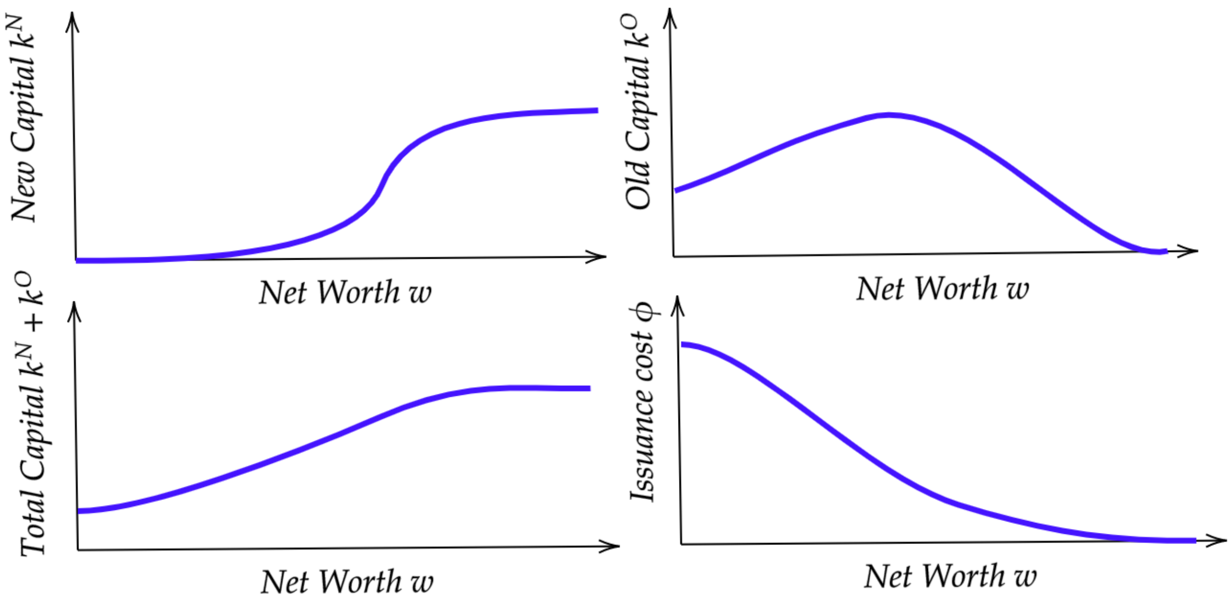
The bottom left panel shows that total capital investment intuitively increases with net worth due to financial constraints. However, an important aspect of this model of capital reallocation is that different firms use different capital vintages. Empirically, there is support for this idea. Using firm age as proxy, there is robust evidence that young firms use old capital [Ma et al., 2022, Eisfeldt and Rampini, 2007].

## 4.3 Effects of Capital Supply Shock

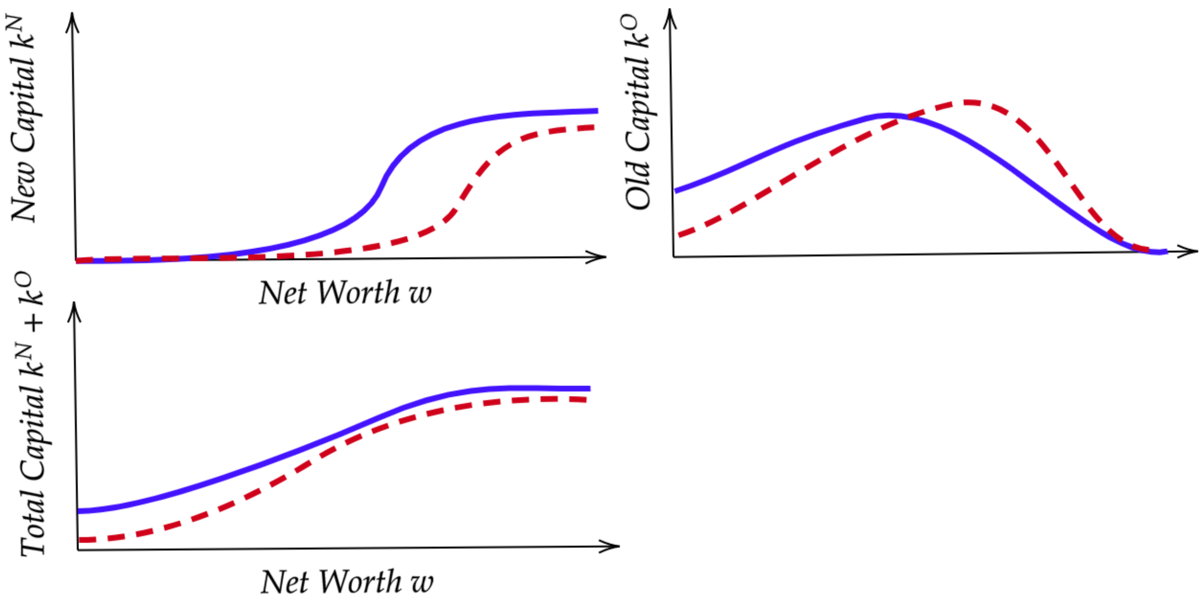
The bottom half of Figure 2 shows the effects of a negative supply shock to new capital.[12] The dotted lines represent the new capital investments made by firms. The first effect is a decrease

[11] One caveat of this stylized model is that it does not explicitly incorporate trading friction in secondary markets (i.e., search costs). Extending the model would allow us to connect more directly to the evidence in the first part of the paper.

[12] Note that we do not include formal proofs. This section is meant to illustrate intuitive predictions, but we cannot rule out that different assumptions would lead to a different equilibrium. Our evidence suggests that a general theory of capital supply shocks is an important area for further research but is outside the scope of the current paper.




(a) Before Supply Shock




(b) After Supply Shock

Figure 2: Illustrative Framework: Capital Choices Across Firms

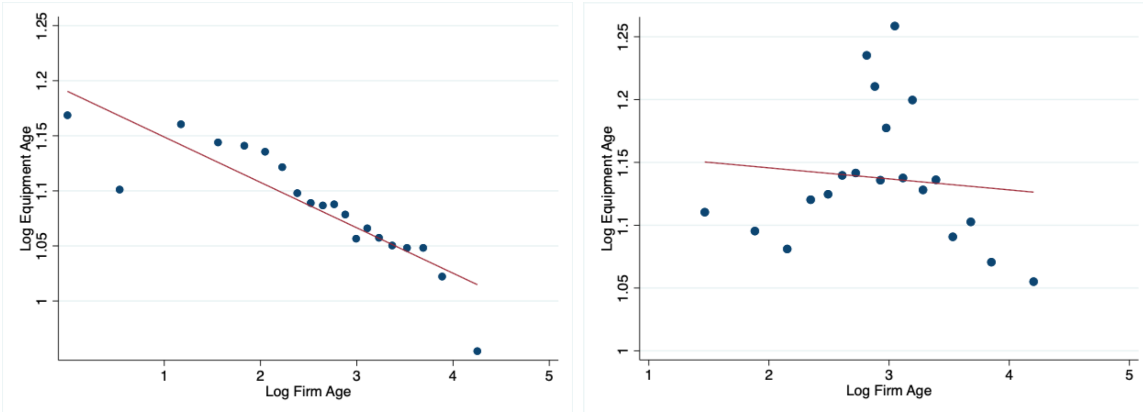
in the number of firms that invest in new capital, as can be seen in the top left panel. The least financially constrained firms can still afford new capital, even if they optimally invest a lower amount. However, some of the firms in the intermediate group of net worth can no longer afford new capital and thus now rely more on used capital. Importantly, this has a spillover effect on the most constrained firms. Because the supply of used capital is inelastic, as it is simply equal to the stock of new capital from the previous period, the price for used capital increases. In equilibrium, that implies that firms with low net worth reduce their investment in used capital as they are crowded out by additional demand from firms in the intermediate group (top right panel). Interestingly, this spillover effect implies that the most financially constrained firms are the ones most affected by the supply shock, even if they do not purchase new capital. The bottom left panel shows that they face the larger drop in investment. While a surge in secondary markets is useful for some firms to dampen the effect of the shock, it also crowds out others. This is a direct consequence of the "distributive externalities" through secondary markets identified in Dávila and Korinek [2018] and Lanteri and Rampini [2021].

This illustrative framework generates two main empirical predictions: after the shock, (1) firms in the intermediate group experience the largest change in the age of their capital investment; and (2) firms in the bottom group experience the largest drop in total investment. We now turn to testing these two predictions in our micro-data.

# 5 Distributive Effects: Empirical Evidence

## 5.1 Change in the Firm Age–Capital Age Gradient

We first examine the correlation between firm age and capital age before and during the supply chain disruption. Figure 3 displays scatterplots of the log of firm age against log equipment age in our sample, controlling for county-by-equipment family fixed effects. The left panel focuses on the pre-November 2021 period. During this time, we see a clear monotonic relationship: younger firms invest in older capital. This replicates the results of Ma et al. [2022], which uses




(a) Normal times (b) Post Oct 2021

Figure 3: Firm Age–Capital Age Gradient

**Notes:** This figure displays binned scatterplots of log firm age against log equipment age. The values are residualized after controlling for county-by-equipment family fixed effects. The sample includes all contracts, divided into two time periods before and after October 2021.

an earlier version of the EDA data.

The right panel Figure 3 shows a drastically different picture after November 2021. The firms in the intermediate group of age experience the largest change in the age of their equipment. This is in line with the first prediction of the model: intermediate firms are the ones that switch the most aggressively from new capital to used capital after the shock.

## 5.2 Investment in Used Capital Across Firm Age Distribution

The previous test focused on changes in equipment age conditional on investing. In this section and the next, we study changes in the dynamics of investment *volume* across the firm distribution. To this end, we aggregate our micro-data to a monthly time series of investment volume for different market segments. In this subsection, we focus on used capital investment. Specifically, we aggregate the number of transactions at the equipment code $\times$ firm age group $\times$ state $\times$ month $\times$ year level. We include three age groups based on the previous scatterplots: (1) firms between one and three years old;[13] (2) firms between four and 29 years old; and (3)

[13]We exclude brand new firms (less than one year old) because our dataset ends in March 2022 and therefore we cannot observe a full year's worth of new firms for 2022.

firms 30 or more years old. For example, we construct a monthly time series of the number of used trucks of a specific type purchased by firms three years old or younger in Maryland. We then combine these different monthly time series in a more aggregate sample to study the dynamics of investment volume after the shock for different firm groups.

We run the following regression:

$$UsedCapital_{e,a,s,t} = \Sigma_g \beta_g \mathbf{1}\{\text{Post Nov 21}\} \times AgeGroup(g) + \nu^e + u^t + \varepsilon^{e,a,s,t}$$

The coefficients of interest are the interactions $\{\beta_g\}_g$ between a post November 2021 indicator with age group dummies. They measure how much used capital investment changed for a specific group of firms. Note that the third age category is subsumed by our fixed effects. The $\{\beta_g\}_g$ coefficients thus represent the change in used investment for an age group *relative* to the oldest firms, which we take as the closest to an unconstrained investment benchmark. The sample includes all contracts for used equipment from January 2019 to February 2022.

Table 6 presents the results. Column 1 includes equipment code and month $\times$ year fixed effects, while Column 2 adds state $\times$ month $\times$ year and firm age fixed effects. The first row shows that the youngest firms experienced the largest drop in used capital investment. The economic magnitudes are large: according to Column 1, their used investment volume dropped by 10 percentage points more than for the oldest firms. In line with the first model's predictions, the second row shows that firms in the intermediate group actually *increased* their investment in used capital relative to the oldest firms (although the effect gets statistically weaker with more fixed effects). These contrasting dynamics are in line with the distributive effects highlighted above.

## 5.3 Total Investment Across Firm Age Distribution

Finally, we run a similar analysis to the above but now consider total investment, defined as the sum of used plus new capital investment in each segment. We run the same regression

| | (1) Log Used Capital | (2) Log Used Capital |
|---|---|---|
| Post Nov 21 x Firm Age Below 4y | -0.104** | -0.128*** |
| | [-2.69] | [-3.29] |
| Post Nov 21 x Firm Age Btw 4 and 29y | 0.016** | 0.014 |
| | [2.08] | [1.50] |
| Firm Age Below 4y | -0.162*** | |
| | [-14.02] | |
| Firm Age Btw 4 and 29y | 0.294*** | |
| | [77.56] | |
| Observations | 318765 | 318757 |
| Adjusted $R^2$ | 0.311 | 0.375 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Investment in Used Capital Across Firm Age Distribution

**Notes:** This table models the number of transactions for used equipment as a function of time and borrower age. Post Nov 21 is an indicator for months starting in November 2021. We measure borrower age using indicator variables for borrowers 3 years or younger, 4–29 years old, or at least 30 years old. The unit of observation is state-equipment code-firm age group-month-year. Fixed effects in each column: (1) equipment code and month × year; (2) equipment code, age, and state × month × year. The sample includes all contracts for used equipment from January 2019 to February 2022. Standard errors are clustered by month-year.

specification:

$$TotalCapital_{e,a,s,t} = \Sigma_g \mathbf{1}\{\text{Post Nov 21}\} \times AgeGroup(g) + \nu^e + u^t + \varepsilon^{e,a,s,t}$$

Table 7 presents the results. We find support for the model's second prediction. The first row shows that the youngest firms experienced the largest drop in total capital investment relative to other firms. The economic magnitudes are again large: their total investment volume dropped by 17 to 21 percentage points relative to others. On the other hand, the second row shows that firms in the intermediate group actually did not experience a similar decline in total investment. This pattern is consistent with secondary markets being used by some firms to dampen the shock, eventually crowding out other firms. Our evidence provides empirical support for distributive externalities emphasized in recent macroeconomic theory literature [Dávila and Korinek, 2018, Lanteri and Rampini, 2021] in the context of a recent large macroeconomic event.

| | (1) Log Total Capital | (2) Log Total Capital |
|---|---|---|
| Post Nov 21 x Firm Age Below 4y | -0.170*** | -0.205*** |
| | [-4.54] | [-4.99] |
| Post Nov 21 x Firm Age Btw 4 and 29y | 0.008 | 0.004 |
| | [1.54] | [0.70] |
| Firm Age Below 4y | -0.356*** | |
| | [-26.43] | |
| Firm Age Btw 4 and 29y | 0.277*** | |
| | [72.10] | |
| Observations | 318765 | 318757 |
| Adjusted $R^2$ | 0.389 | 0.470 |

$t$ statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Total Capital Investment Across Firm Age Distribution

**Notes:** This table models the number of equipment transactions as a function of time and borrower age. Post Nov 21 is an indicator for months starting in November 2021. We measure borrower age using indicator variables for borrowers 3 years or younger, 4–29 years old, or at least 30 years old. The unit of observation is state-equipment code-firm age group-month-year. Fixed effects in each column: (1) equipment code and month × year; (2) equipment code, age, and state × month × year. The sample includes all contracts from January 2019 to February 2022. Standard errors are clustered by month-year.

## 5.4 Robustness

**Sample selection:** One limitation of our sample is that by construction it is restricted to equipment with a lien and thus excludes transactions in which the buyer fully paid in cash. A potential concern is this sample selection drives our results. For instance, it might exclude young firms that actually invested during the supply chain disruptions but paid in cash.

Several factors alleviate this concern. First, at a general level, Ma et al. [2022] provide multiple forms of evidence that the UCC data are representative of the distribution of U.S. firms in their sample period of 1990–2017, which largely overlaps with ours. Second, if anything, the UCC sample selection likely overweights younger firms, as it is well known that they are more likely to finance capital investment. Similarly, secured financing tends to become more common during economic downturns [Benmelech et al., 2020]. On a priori grounds, this would reduce the concern of young firms that actually invested in the fall of 2021 being excluded from our sample because they disproportionately paid in cash.

Third, we conduct additional tests assessing the sensitivity of our results to different specification choices that consider selection in different ways. To start, we find that the results are robust to adding progressively tighter fixed effects, which we do in an attempt to control for the borrower's decision to finance equipment. Tables IA.2 and IA.3 in the Internet Appendix show that if anything, our results strengthen as we begin controlling for time and equipment effects, suggesting that our results are not driven by borrower unobservables correlated with selection into secured financing.

Fourth, we run weighted least squares tests to re-weight observations in a way that mitigates sample selection. Tables IA.4 and IA.5 re-weight observations based on the distribution of equipment at wholesalers each year, following the idea of Ma et al. [2022].[14] Intuitively, by observing the nature and location of inventory that wholesalers obtain financing for in a given year, we can develop a proxy for the population of equipment entering the market, regardless of whether the ultimate user financed the purchase or paid cash. Regardless of whether we use weights based on location, equipment code, or both, we find a significant investment drop for the youngest firms during the supply chain disruption.

**Young firms' demand for capital:** A related concern is that our results simply reflect a decline in capital demand by young firms instead of the spillover effects of the supply chain disruption. To test this directly, we revisit our secondary market tests, and introduce an interaction term for the youngest firms. Intuitively, if young firms reduced their demand for capital, then we should not observe the same search behavior as we found for the full sample: young firms would not go to the effort to travel further or increasingly acquire capital from fundamentally different firms. However, Table IA.8 shows no statistical difference for young firms in terms of the distance from the previous equipment user. Table IA.9 finds some evidence that, if anything, young firms were *more* likely to acquire equipment from less similar firms during the supply chain disruptions. Together, this evidence contradicts interpretations based on young firms experiencing a disproportionate demand decrease for capital.

Other evidence from outside our setting does not support the view that young firms'

[14] These wholesale acquisitions are primarily floor-plan financing for dealer inventory. Recall that these wholesale buyers are excluded from our main sample as our focus is on end users of equipment.

investment demand was especially low as the recovery started in 2021. For instance, the Kansas City Fed Small Business Lending Survey shows that loan demand was high in 2021–22 after dropping throughout 2020, in part due to supply chain disruptions.[15] In addition, the introduction of the large Paycheck Protection Program in 2020 specifically supported small firms' finances.[16] More than $950 billion of loans were provided over three rounds from April 2020 to May 2021. Although the program focused on payroll relief, if anything the additional liquidity could have helped support firms' investment demand when the recovery arrived. This extra liquidity, combined with the program's focus on small firms, makes it unlikely that young firms experienced a large decline in their demand for capital that would explain our findings.

**Heterogeneous effects of market liquidity:** As additional support for the mechanism, we conduct a further cross-sectional test. We split the sample based on secondary market liquidity. We use the time between transactions as a measure of liquidity and classify equipment codes with a median time between repeat sales above one year as low-liquidity segments, the others being high-liquidity segments. Tables IA.6 and IA.7 in the Internet Appendix show the results for this sample split. As expected given our mechanism, the results are generally stronger in the low liquidity segments.

**Financing channel:** We conduct two additional tests to gauge whether a financing channel might explain our main results. First, we split the sample by lender type to compare banks and nonbanks. It is well understood that nonbanks have a large presence in the equipment market, but they respond differently to economic shocks and face little regulation [Murfin and Pratt, 2019, Gopal and Schnabl, 2020]. If the capital reallocation we document is driven by a financing channel as opposed to supply chain disruptions, then one might expect different

[15] See Chart 9 of the 2022Q1 issue: `https://www.kansascityfed.org/Research/documents/8864/Kansas-City-Fed-Small-Business-Lending-Survey-Quarter-1-2022.pdf`.

[16] The Paycheck Protection Program, initiated over a year before our supply chain disruption period, provided small businesses with loans to cover up to eight weeks of payroll costs during the pandemic. The loans were fully forgivable, so long as the firm maintained headcount and salary levels. The program targeted firms with 500 or fewer employees, though there were some exceptions for larger firms in specific industries. Participating firms had to be established before February 15, 2020 (i.e., one could not incorporate and legally receive a loan from the program).

patterns for transactions financed by banks and nonbanks.[17] To examine this, we split lenders into bank and nonbank categories using Gopal and Schnabl's (2022) algorithm. Tables IA.10 and IA.11 in the Internet Appendix show our results are similar across the two lender types, suggesting that this financing channel cannot explain our results.

Moreover, we investigate whether similar results hold for the 2008–09 crisis, when financing was severely disrupted but supply chains were not. Tables IA.12 and IA.13 in the Internet Appendix show that this is not the case. There is no similar pattern in investment in new and used capital across the firm distribution. This is consistent with the 2008-09 crisis being dominated by financing and productivity shocks, rather than a large supply shock like the one observed during the pandemic.

# 6 Discussion

Our analysis focuses on investment and capital reallocation dynamics following the large-scale production disruptions of 2021. The results of Ma et al. [2022] suggest that the drop in investment we document for small firms might have significant real effects. They document that a reduction in the availability of used capital leads to less start-up entry, less job creation, and less growth for small firms. Moreover, the effects of the supply shock are likely to be persistent as they permanently lowered the stock of used capital. Our current sample ends in early 2022 and is thus too short to investigate these effects directly.

Another interesting aspect of this episode is the role that financial contracting might have played in amplifying the shock. Specifically, the capital transactions we study are at least in part financed by lenders either as collateralized loans or leases. Interestingly, this contracting feature can imply financial frictions in asset *sales* given that capital users do not (or, do not fully) own the assets [Donaldson et al., 2021]. The incentives to sell in the face of high prices are muted by these control rights issues, potentially exacerbating a secondary market price surge. Understanding better the strength of this mechanism in this context is an important

[17] For instance, banks, who benefit from government safety nets, received large inflows of deposits in 2020.

avenue for future research.

Finally, one open question relates to the potential for public intervention. Lanteri and Rampini [2021] document distributive externalities in capital reallocation and show that subsidies for new investment can increase welfare. Investment subsidies are commonly used in practice although their optimal design is not yet well understood. In the context of the production shock of 2021, it is unclear if special subsidies for investment in *new* capital would have been effective in alleviating the shock in the short-term: the demand for new equipment was already vastly in excess of available supply. A potential alternative might have introduced exceptional subsidies for investment in *used* capital. On its face, this seems like it could have helped smaller and younger firms facing high prices in secondary markets. However, these subsidies need to be properly targeted: if they are too broad they might actually exacerbate crowding out by increasing competition in secondary markets even further. Our evidence shows the practical challenge in designing these policies and the need to think about their implications on equilibrium capital reallocation to avoid perverse effects.

# 7 Conclusion

This paper uses rich micro-data on capital transactions to study the equilibrium effects of a large macroeconomic supply shock on firms' investment. We document that a surge in secondary market activity dampened the shock for some firms, but priced out others. In equilibrium, the youngest firms were the most affected by the shock even though they rarely purchase new capital. These results highlight the key role of secondary markets and distributive effects for small business investment. Some of the economic forces we document are relevant in other settings, such as for other markets for consumer durable goods and assets, and we leave these extensions for future research.

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# Internet Appendix - Additional Figures and Tables

| | (1) New Equipment | (2) New Equipment |
|---|---|---|
| Deere x Strike | -0.081** | -0.077** |
| | [-2.64] | [-2.64] |
| Observations | 3055351 | 3055344 |
| Adjusted $R^2$ | 0.263 | 0.279 |

$t$ statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Notes:** Column 1 fixed effects: county, equipment code-month-year, manufacturer; column 2 fixed effects: county, equipment code-month-year, manufacturer, state-month-year.

Table IA.1: John Deere Strike: Share of New Equipment

| | (1) Log Used Capital | (2) Log Used Capital | (3) Log Used Capital | (4) Log Used Capital |
|---|---|---|---|---|
| Post Nov 21 x Firm Age Below 4y | -0.055* | -0.050 | -0.102** | -0.104** |
| | [-1.79] | [-1.67] | [-2.69] | [-2.69] |
| Post Nov 21 x Firm Age Btw 4 and 29y | 0.004 | 0.003 | 0.014 | 0.016** |
| | [0.45] | [0.32] | [1.65] | [2.08] |
| Post Nov 21 | 0.024* | 0.023 | 0.024 | |
| | [1.83] | [1.66] | [1.60] | |
| Firm Age Below 4y | -0.072*** | -0.103*** | -0.161*** | -0.162*** |
| | [-7.52] | [-10.90] | [-14.01] | [-14.02] |
| Firm Age Btw 4 and 29y | 0.235*** | 0.233*** | 0.293*** | 0.294*** |
| | [62.65] | [62.27] | [77.56] | [77.56] |
| Observations | 318778 | 318777 | 318765 | 318765 |
| Adjusted $R^2$ | 0.026 | 0.088 | 0.309 | 0.311 |

$t$ statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.2: Investment in Used Capital Across Firm Age Distribution: Alternative FEs

**Notes:** This table models the log number of used equipment transactions on the interaction of a post November 2021 indicator with firm age group dummies. The unit of observation is state-equipment code-firm age group-month-year. Fixed effects: Column 1: year and month; column 2: year, month, and equipment family; column 3: year, month, and equipment code; column 4: month $\times$ year and equipment code. Standard errors are clustered by month-year.

| | (1) Log Total Capital | (2) Log Total Capital | (3) Log Total Capital | (4) Log Total Capital |
|---|---|---|---|---|
| Post Nov 21 x Firm Age Below 4y | -0.065*** | -0.062*** | -0.168*** | -0.170*** |
| | [-2.93] | [-2.89] | [-4.56] | [-4.54] |
| Post Nov 21 x Firm Age Btw 4 and 29y | 0.001 | -0.001 | 0.006 | 0.008 |
| | [0.13] | [-0.15] | [0.88] | [1.54] |
| Post Nov 21 | -0.011 | -0.011 | 0.006 | |
| | [-0.96] | [-0.93] | [0.41] | |
| Firm Age Below 4y | -0.213*** | -0.221*** | -0.355*** | -0.356*** |
| | [-27.91] | [-27.78] | [-26.48] | [-26.43] |
| Firm Age Btw 4 and 29y | 0.179*** | 0.195*** | 0.277*** | 0.277*** |
| | [54.45] | [55.62] | [72.16] | [72.10] |
| Observations | 318778 | 318777 | 318765 | 318765 |
| Adjusted $R^2$ | 0.026 | 0.087 | 0.387 | 0.389 |

$t$ statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.3: Total Capital Investment Across Firm Age Distribution: Alternative FEs

**Notes:** This table models the log number of equipment transactions on the interaction of a post November 2021 indicator with firm age group dummies. The unit of observation is state-equipment code-firm age group-month-year. Fixed effects: Columns 1: year and month; column 2: year, month, and equipment family; column 3: year, month, and equipment code; column 4: month × year and equipment code. Standard errors are clustered by month-year.

| | (1) Log Used Capital | (2) Log Used Capital | (3) Log Used Capital | (4) Log Used Capital | (5) Log Used Capital | (6) Log Used Capital |
|---|---|---|---|---|---|---|
| Post Nov 21 x Firm Age Below 4y | -0.104** | -0.128*** | -0.045 | -0.209*** | -0.133** | -0.215*** |
| | [-2.69] | [-3.29] | [-0.51] | [-2.74] | [-2.37] | [-3.34] |
| Post Nov 21 x Firm Age Btw 4 and 29y | 0.016** | 0.014 | 0.100 | 0.081 | 0.060** | 0.072** |
| | [2.08] | [1.50] | [1.65] | [1.55] | [2.10] | [2.42] |
| Firm Age Below 4y | -0.162*** | | -0.283*** | | -0.257*** | |
| | [-14.02] | | [-10.85] | | [-12.06] | |
| Firm Age Btw 4 and 29y | 0.294*** | | 0.589*** | | 0.632*** | |
| | [77.56] | | [38.91] | | [75.19] | |
| Observations | 318765 | 318757 | 67145 | 67092 | 67145 | 67092 |
| Adjusted $R^2$ | 0.311 | 0.375 | 0.334 | 0.554 | 0.375 | 0.516 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.4: Investment in Used Capital Across Firm Age Distribution: Reweighting with Wholesaler weights

**Notes:** This table models the log number of used equipment transactions on the interaction of a post November 2021 indicator with firm age group dummies. The unit of observation is state-equipment code-firm age group-month-year. Columns 1 and 2 are the baseline specification; columns 3 and 4 are WLS using equipment code x state x year weights for wholesalers' used equipment; columns 5 and 6 are WLS using equipment family x state x year weights for wholesalers' used equipment. Fixed effects in each column: (1, 3, and 5) equipment code and month × year; (2, 4, and 6) equipment code, age, and state × month × year. Standard errors are clustered by month-year.

| | (1) Log Total Capital | (2) Log Total Capital | (3) Log Total Capital | (4) Log Total Capital | (5) Log Total Capital | (6) Log Total Capital |
|---|---|---|---|---|---|---|
| Post Nov 21 x Firm Age Below 4y | -0.170*** | -0.205*** | -0.214*** | -0.347*** | -0.228*** | -0.317*** |
| | [-4.54] | [-4.99] | [-3.01] | [-4.85] | [-4.05] | [-4.84] |
| Post Nov 21 x Firm Age Btw 4 and 29y | 0.008 | 0.004 | -0.005 | 0.006 | 0.014 | 0.037 |
| | [1.54] | [0.70] | [-0.08] | [0.13] | [0.64] | [1.66] |
| Firm Age Below 4y | -0.356*** | | -0.536*** | | -0.472*** | |
| | [-26.43] | | [-20.16] | | [-23.13] | |
| Firm Age Btw 4 and 29y | 0.277*** | | 0.541*** | | 0.594*** | |
| | [72.10] | | [38.87] | | [95.95] | |
| Observations | 318765 | 318757 | 67145 | 67092 | 67145 | 67092 |
| Adjusted $R^2$ | 0.389 | 0.470 | 0.363 | 0.624 | 0.443 | 0.616 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.5: Total Capital Investment Across Firm Age Distribution: Reweighing with Wholesaler weights

**Notes:** This table models the log number of equipment transactions on the interaction of a post November 2021 indicator with firm age group dummies. The unit of observation is state-equipment code-firm age group-month-year. Columns 1-2 are the baseline specification; columns 3-4 are WLS using equipment code x state x year weights for wholesalers' used equipment; columns 5-6 are WLS using equipment family x state x year weights for wholesalers' used equipment. Fixed effects in each column: (1, 3, and 5) equipment code and month × year; (2, 4, and 6) equipment code, age, and state × month × year. Standard errors are clustered by month-year.

| | (1) Log Used Capital | (2) Log Used Capital |
|---|---|---|
| Post Nov 21 x Firm Age Below 4y | -0.125** | -0.017 |
| | [-2.62] | [-0.66] |
| Post Nov 21 x Firm Age Btw 4 and 29y | 0.025* | -0.000 |
| | [1.73] | [-0.02] |
| Firm Age Below 4y | -0.195*** | -0.053*** |
| | [-15.63] | [-5.56] |
| Firm Age Btw 4 and 29y | 0.368*** | 0.148*** |
| | [86.04] | [27.82] |
| Observations | 215257 | 103508 |
| Adjusted $R^2$ | 0.356 | 0.142 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.6: Investment in Used Capital Across Firm Age Distribution: By Secondary Market Liquidity

**Notes:** This table models the log number of used equipment transactions on the interaction of a post November 2021 indicator with firm age group dummies. The unit of observation is state-equipment code-firm age group-month-year. Column 1 includes only equipment codes with low secondary market liquidity, defined as having a median time between repeat sales above one year; while Column 2 includes the rest of the sample. All specifications include month × year and equipment code fixed effects. Standard errors are clustered by month-year.

| | (1) Log Total Capital | (2) Log Total Capital |
|---|---|---|
| Post Nov 21 x Firm Age Below 4y | -0.193*** | -0.094*** |
| | [-4.22] | [-2.77] |
| Post Nov 21 x Firm Age Btw 4 and 29y | 0.012 | 0.003 |
| | [1.49] | [0.23] |
| Firm Age Below 4y | -0.395*** | -0.230*** |
| | [-26.78] | [-21.85] |
| Firm Age Btw 4 and 29y | 0.352*** | 0.131*** |
| | [76.34] | [31.22] |
| Observations | 215257 | 103508 |
| Adjusted $R^2$ | 0.402 | 0.346 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.7: Total Capital Investment Across Firm Age Distribution: By Secondary Market Liquidity

**Notes:** This table models the log number of equipment transactions on the interaction of a post November 2021 indicator with firm age group dummies. The unit of observation is state-equipment code-firm age group-month-year. Column 1 includes only equipment codes with low secondary market liquidity, defined as having a median time between repeat sales above one year; while Column 2 includes the rest of the sample. All specifications include month × year and equipment code fixed effects. Standard errors are clustered by month-year.

| | (1)<br>Log Time Since Last Contract | (2)<br>Log Time Since Last Contract | (3)<br>Log Distance | (4)<br>Log Distance | (5)<br>Same County | (6)<br>Same County |
|---|---|---|---|---|---|---|
| Year 2021/2 | -0.156*** | | 0.030 | | -0.014*** | |
| | [-11.36] | | [1.26] | | [-2.76] | |
| Firm Age Below 4y | 0.027** | 0.028** | -0.062*** | -0.062*** | 0.016*** | 0.016*** |
| | [2.47] | [2.54] | [-4.20] | [-4.20] | [5.23] | [5.25] |
| Firm Age Btw 4 and 29y | -0.004 | -0.004 | -0.026*** | -0.026*** | 0.013*** | 0.013*** |
| | [-0.50] | [-0.51] | [-2.67] | [-2.67] | [6.07] | [6.07] |
| Year 2021/2 x Firm Age Below 4y | -0.075 | | -0.095 | | 0.002 | |
| | [-0.72] | | [-0.74] | | [0.09] | |
| Year 2021 | | -0.134*** | | 0.041* | | -0.014*** |
| | | [-9.19] | | [1.65] | | [-2.68] |
| Year 2021 x Firm Age Below 4y | | -0.079 | | -0.087 | | -0.001 |
| | | [-0.73] | | [-0.67] | | [-0.06] |
| Observations | 205794 | 205794 | 239497 | 239497 | 250713 | 250713 |
| Adjusted $R^2$ | 0.457 | 0.457 | 0.464 | 0.464 | 0.337 | 0.337 |

$t$ statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## Table IA.8: Trading Activity in Used Capital: Young Firm Interactions

**Notes:** This table models secondary market activity as a function of time and an indicator for the age of the acquiring firm. The unit of observation is a transaction for a particular piece of equipment. The dependent variable in Columns 1 and 2 is the log of days between the last two transactions for that equipment; in columns 3 and 4 it is the log number of miles between the counties of the last two users of that equipment; columns 5 and 6 use an indicator variable for the same county instead of log distance. All specifications include equipment serial number, county and calendar month fixed effects, as well as equipment age (in year) indicators. The sample includes all equipment that transacted at least twice. Standard errors are clustered by serial number.

| | (1)<br>Same SIC2 | (2)<br>Same SIC2 | (3)<br>Same Modal Equipment Code | (4)<br>Same Modal Equipment Code | (5)<br>Same Modal Equipment Family | (6)<br>Same Modal Equipment Family |
|---|---|---|---|---|---|---|
| Year 2021/2 | -0.015** | | -0.010* | | -0.010*** | |
| | [-2.24] | | [-1.69] | | [-2.83] | |
| Firm Age Below 4y | 0.013*** | 0.013*** | 0.010** | 0.010*** | 0.002 | 0.002 |
| | [3.17] | [3.15] | [2.57] | [2.58] | [0.95] | [1.01] |
| Firm Age Btw 4 and 29y | 0.005* | 0.005* | 0.003 | 0.003 | -0.002 | -0.002 |
| | [1.78] | [1.77] | [1.00] | [1.00] | [-1.42] | [-1.42] |
| Year 2021/2 x Firm Age Below 4y | 0.014 | | -0.045 | | -0.029 | |
| | [0.45] | | [-1.57] | | [-1.43] | |
| Year 2021 | | -0.020*** | | -0.008 | | -0.007* |
| | | [-2.91] | | [-1.25] | | [-1.82] |
| Year 2021 x Firm Age Below 4y | | 0.019 | | -0.048 | | -0.036* |
| | | [0.62] | | [-1.61] | | [-1.70] |
| Observations | 250713 | 250713 | 250713 | 250713 | 250713 | 250713 |
| Adjusted $R^2$ | 0.265 | 0.265 | 0.346 | 0.346 | 0.464 | 0.464 |

$t$ statistics in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## Table IA.9: Trading Activity in Used Capital Across Sectors and Main Equipment: Young Firm Interactions

**Notes:** This table models secondary market activity as a function of time and an indicator for the age of the acquiring firm. The unit of observation is a transaction for a particular piece of equipment. The dependent variable in Columns 1 and 2 is an indicator equal to 1 if the last two users of that equipment are in the same two-digit SIC code; in columns 3 and 4 it is an indicator equal to 1 if the last two users of that equipment share the same model equipment code (defined over their previous transactions); columns 5 and 6 use equipment family instead of equipment code. All specifications include serial number, county and calendar month fixed effects, as well as equipment age (in year) indicators. The sample includes all equipment that transacted at least twice. Standard errors are clustered by serial number.

| | (1) Log Used Capital | (2) Log Used Capital |
|---|---|---|
| Post Nov 21 x Firm Age Below 4y | -0.096* | -0.103*** |
| | [-1.91] | [-3.51] |
| Post Nov 21 x Firm Age Btw 4 and 29y | 0.021* | 0.012 |
| | [1.88] | [1.06] |
| Firm Age Below 4y | -0.125*** | -0.180*** |
| | [-9.95] | [-14.90] |
| Firm Age Btw 4 and 29y | 0.214*** | 0.361*** |
| | [30.04] | [71.36] |
| Observations | 138131 | 180625 |
| Adjusted $R^2$ | 0.246 | 0.367 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.10: Investment in Used Capital Across Firm Age Distribution: By Lender Type

**Notes:** This table models the log number of used equipment transactions on the interaction of a post November 2021 indicator with firm age group dummies. The unit of observation is state-equipment code-firm age group-month-year. Column 1 (2) includes only contracts from markets where banks originate more (less) than half of contracts. All specifications include Month $\times$ year and equipment code fixed effects. Standard errors are clustered by month-year.

| | (1) Log Total Capital | (2) Log Total Capital |
|---|---|---|
| Post Nov 21 x Firm Age Below 4y | -0.114*** | -0.194*** |
| | [-3.18] | [-5.49] |
| Post Nov 21 x Firm Age Btw 4 and 29y | 0.031** | -0.011 |
| | [2.46] | [-1.19] |
| Firm Age Below 4y | -0.297*** | -0.373*** |
| | [-23.86] | [-25.25] |
| Firm Age Btw 4 and 29y | 0.173*** | 0.358*** |
| | [27.84] | [60.82] |
| Observations | 138131 | 180625 |
| Adjusted $R^2$ | 0.354 | 0.404 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.11: Total Capital Investment Across Firm Age Distribution: By Lender Type

**Notes:** This table models the log number of equipment transactions on the interaction of a post November 2021 indicator with firm age group dummies. The unit of observation is state-equipment code-firm age group-month-year. Column 1 (2) includes only contracts from markets where banks originate more (less) than half of contracts. All specifications include month $\times$ year and equipment code fixed effects. Standard errors are clustered by month-year.

| | (1) Log Used Capital | (2) Log Used Capital |
|---|---|---|
| 2008-09 x Firm Age Below 4y | 0.074*** | 0.002 |
| | [5.53] | [0.09] |
| 2008-09 x Firm Age Btw 4 and 29y | -0.011* | 0.010 |
| | [-1.79] | [1.31] |
| Firm Age Below 4y | -0.051*** | 0.013 |
| | [-10.53] | [0.58] |
| Firm Age Btw 4 and 29y | 0.289*** | 0.270*** |
| | [156.27] | [54.19] |
| Observations | 2296325 | 392714 |
| Adjusted $R^2$ | 0.306 | 0.358 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.12: Investment in Used Capital Across Firm Age Distribution: the 2008-09 Crisis

**Notes:** This table models the log number of used equipment transactions on the interaction of a 2008-09 indicator with firm age group dummies. The unit of observation is state-equipment code-firm age group-month-year. Column 1 (2) includes all years (only contracts from 2007-10) All specifications include month $\times$ year and equipment code fixed effects. Standard errors are clustered by month-year.

| | (1) Log Total Capital | (2) Log Total Capital |
|---|---|---|
| 2008-09 x Firm Age Below 4y | 0.056*** | -0.015 |
| | [3.76] | [-0.54] |
| 2008-09 x Firm Age Btw 4 and 29y | -0.005 | 0.002 |
| | [-1.12] | [0.34] |
| Firm Age Below 4y | -0.214*** | -0.137*** |
| | [-33.17] | [-5.71] |
| Firm Age Btw 4 and 29y | 0.258*** | 0.253*** |
| | [154.40] | [41.32] |
| Observations | 2296325 | 392714 |
| Adjusted $R^2$ | 0.357 | 0.366 |

$t$ statistics in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA.13: Total Capital Investment Across Firm Age Distribution: the 2008-09 Crisis

**Notes:** This table models the log number of equipment transactions on the interaction of a 2008-09 indicator with firm age group dummies. The unit of observation is state-equipment code-firm age group-month-year. Column 1 (2) includes all years (only contracts from 2007-10). All specifications include month $\times$ year and equipment code fixed effects. Standard errors are clustered by month-year.