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Who Finances Durable Goods and Why It Matters: Captive Finance and the Coase Conjecture

JUSTIN MURFIN and RYAN PRATT*

ABSTRACT

We propose that, by financing their own product sales through captive finance subsidiaries, durable goods manufacturers commit to higher resale values for their products in future periods. Using data on captive financing by the manufacturers of heavy equipment, we find that captive-backed models have lower price depreciation. The evidence is consistent with captive finance helping manufacturers commit to ex-post actions that support used machine prices. This, in turn, conveys higher pledgeability for captive-backed products, even for individual machines financed by banks. Although motivated as a rent-seeking device, captive financing generates positive spillovers by relaxing credit constraints.

A SUBSTANTIAL SHARE OF DURABLE goods financed with credit in the United States is not financed by banks, but rather by the manufacturer of the good itself. For firms making new investments in equipment used in agriculture, construction, logging, manufacturing, and printing, the share of financing done by the wholly owned subsidiary lenders of equipment manufacturers was 58% as of 2013 and ranged from dominant (76% in agricultural equipment) to nontrivial (18% in printing) (see Figure 1). And while manufacturers are important lenders within each of these industries, they are also sizable enough to be important in aggregate. For example, manufacturing firms such as Toyota, John Deere, and Caterpillar originate loan portfolios in a given year that would rank them among the top banks in terms of business and non-credit card installment lending (as of 2012, #9, 15, and 17, respectively).[1] Recent work by Stroebel (2016)

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[1] This is based on bank holding company call report data, where, for comparability, bank loan portfolios exclude interbank, charge card, and mortgage lending.

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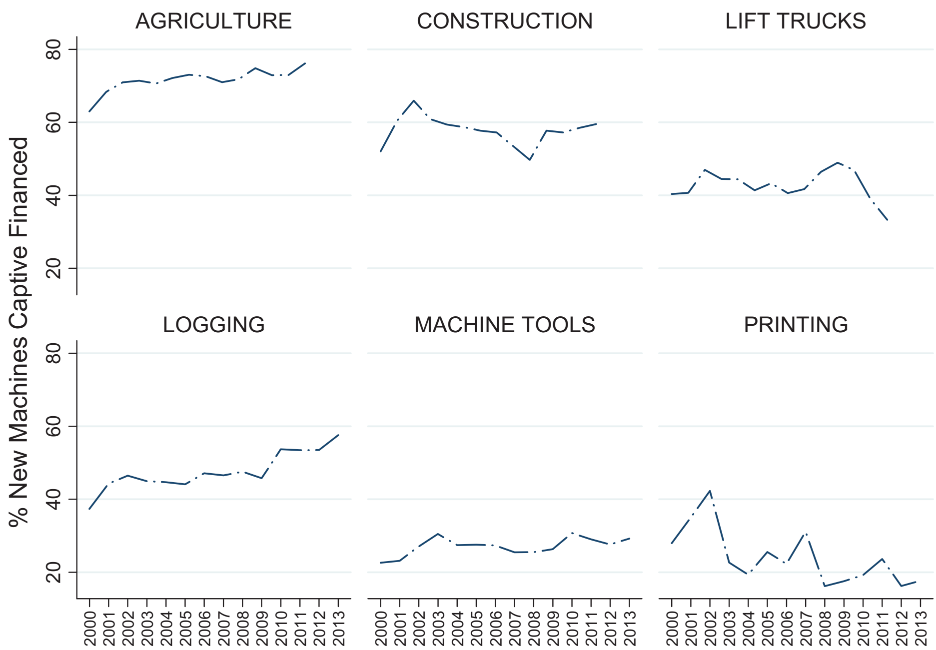

Figure 1. Captive finance and durable investment. The figure plots the percentage of new durable goods investment financed by captive finance subsidiaries of manufacturers in a variety of industries. Industry definitions were chosen by Equipment Data Associates, which provided these summary statistics. (Color figure can be viewed at wileyonlinelibrary.com)

and Benmelech, Meisenzahl, and Ramcharan (2017) further demonstrates the importance of these vertically integrated lenders in the markets for new housing and cars, respectively.

As the line between traditional banking and manufacturing firms' bank-like activities—so-called "captive finance"—is increasingly blurred, a natural question arises. What are the economic motives behind manufacturers financing their own sales? If banks are specialists in credit evaluation, monitoring, and fundraising and thus are natural candidates to finance durable goods investment, what is the comparative advantage of captive finance?

In this paper, we explore a set of candidate answers to the questions above that are informed by the expansive literature on durable goods. We begin with the insight that, because consumers of durables care about the future value of their goods, durable goods producers require credible means of assuring customers that machines bought today will retain their value tomorrow. By linking future periods' profits to the future value of products sold today (whether through collateral value on loans or residual values on leases), captive finance might serve as a way for manufacturers to signal or commit to high future resale values for their product line, supporting rents today.

Following this intuition, we explore the link between who finances capital—whether traditional banks or the manufacturer itself—and realized resale values of the same capital. Combining auction data that allow us to measure depreciation rates for varying makes and models of heavy construction equipment with new data on the financing provided by captives in support of equipment sales, we document a robust link between products' realized depreciation paths and the financing support offered by captive lenders: on average, moving from zero captive financing for a given make and model to machine sales being 100% financed by the manufacturer is associated with a 14 to 20 percentage point decrease in observed depreciation. These results are driven by the source of financing and do not depend on the nature of the financing contract. Captive lending and leasing portfolios are both associated with lower depreciation, but in equilibrium, installment loans are more prevalent.

Given the strong observed correlation between captive financing and the realized price depreciation associated with financed products, we proceed by exploring the potential mechanisms at play. Here, we differentiate between two closely related ideas. On the one hand, we emphasize a new idea to the vendor financing literature: that captive finance may be operating as a solution to the famous Coase conjecture (Coase (1972)). Coase argues that even a monopolist producer of a durable good faces competition from its own future production, as customers may choose to delay their purchases if they expect prices to fall. Absent the ability to commit to future production, this competition can erode the producer's market power, as customers will be unwilling to pay monopolist prices today if they expect prices to fall tomorrow. Bulow (1982) shows that, by leasing rather than selling their products, manufacturers internalize the price impact of their own future production choices, which enables them to commit to higher future prices and thereby boosts buyers' willingness-to-pay today. We argue that this intuition holds for vendor financing more broadly, including both leases and loans. We refer to this explanation as the "commitment" view of captive financing.

This idea is distinct from an intuitive and closely related interpretation: that lower depreciation rates on captive-financed machines are driven by higher ex-ante quality of captive-backed machines (and not the ex-post commitment of their manufacturers), which manifests in longer productive lives and hence slower depreciation. This would arise naturally, for example, in markets with information asymmetry whereby the vendor's choice to finance its own product provides a signal of quality, as suggested in Stroebel (2016), Emery and Nayar (1998), Long, Malitz, and Ravid (1993), and Lee and Stowe (1993). In this case, the association between captive finance and high future resale values may arise through variation in ex-ante unobservable machine characteristics as opposed to (or in addition to) ex-post producer actions. Hereafter, we refer to this explanation as the "information asymmetry" view of captive finance.

While the commitment and information asymmetry hypotheses both predict a relationship between price depreciation and captive finance, we can distinguish the two through a simple decomposition of depreciation, about which the hypotheses produce competing predictions. To see this, notice that the annual depreciation of a given machine (we will use a 2002 John Deere tractor as a motivating example) can be parsed into two distinct pieces: (i) the change in the price of new tractors over time (e.g., an '02 tractor in 2002 versus an '03 tractor in 2003) and (ii) the discount in the prices of used versus new tractors at a given point in time (e.g., an '02 tractor in 2003 versus an '03 tractor in 2003). We refer to the former component of depreciation as "new price depreciation" and the latter as "productivity-driven depreciation," since it arises from the losses in productive capacity as a machine ages.

Importantly, models of information asymmetry predict variation in machine quality that affects depreciation through productivity-driven depreciation: captives signal quality by financing durable machines with longer productive lives, which generates a shallower discount between old and new vintages at a given point in time. Yet, we find no relationship between captive finance and a measure of depreciation based on the cross-sectional covariation between prices and age. This not only undermines hypotheses in which vendors signal ex-ante quality with their financing choices, but more broadly appears inconsistent with *any* story that results in captive-financed machines having greater longevity. In contrast, the commitment view is silent on how financing should vary with productivity-driven measures. Excess production due to limited commitment, for example, will affect both new and used prices at the same time.

We do find, however, that new-price depreciation is strongly related to captive financing, as we would expect under the limited commitment view whereby captives' ex-post production choices affect the price of tomorrow's new (and used) machines relative to the price of today's. For each model, using auction sales of new or close-to-new machines, we estimate the time trend in new prices and compare it to the share of captive financing for that model. We find that going from 0% to 100% captive finance reduces new price depreciation by 16 percentage points.

Finally, for a subset of makes and models, we can approximate the depreciation on "new-old-stock" machines. Here, we estimate depreciation at the model $\times$ vintage level to avoid the potential for confounding changes in the design of new machines over time, while also controlling for changes in machine condition at the time of auction to remove the effects of physical degradation on depreciation. This gives us our sharpest test of the limited commitment hypothesis, allowing us to ask how the value of a hypothetical stock of unused machines from a given model-year will perform in resale markets over time, conditional on the manufacturer's history of financing for that model. Neither controlling for changes in condition nor estimating within model-year has a noticeable impact on captive financing's effect on expected depreciation.

Of course, the limited commitment mechanism depends critically on firms' ability to affect prices—firms without market power have no incentives to use captive financing to commit to prices they cannot control. Earlier findings show that captive finance is concentrated among producers with plausible market power (Mian and Smith (1992), Bodnaruk, O'Brien, and Simonov (2016)). We confirm this result and extend it within-firm to show that manufacturers concentrate their captive financing in machines for which they have high market share. Meanwhile, the relationship between financing and depreciation is limited to markets where producers are relatively large and concentrated.

We next move closer to causal inference in a narrower setting by exploiting a natural experiment that abruptly shifted the share of captive financing for a specific set of equipment models. In 2007, Volvo, which had a large financing arm, acquired a division of Ingersoll Rand, which had a history of very little captive financing. We observe a sharp uptick in resale performance following the acquisition and a corresponding increase in captive financing share by Volvo. Importantly, even used machines produced by Ingersoll Rand prior to the division sale began to retain their value more after the sale, indicating that our results are not being driven by ex-ante machine characteristics such as machine quality.

Although limited commitment can affect prices through a variety of ex-post firm actions (we discuss potential mechanisms at length in Section I.B), the earliest papers on durable goods monopolists focus on production quantities. Using a proxy for new machine sales, we find strongly suggestive evidence of a link between financing and ex-post production. Within a given manufacturer, future sales are significantly lower for equipment types that have a history of captive finance backing.

Our final set of tests explores the implications of captive finance for the behavior of other financial intermediaries. We show that products receiving strong captive backing enjoy lower down payments/higher loan-to-values (LTVs) consistent with their lower depreciation rates. This is true even for individual machines that are financed by bank lenders. These higher LTVs may be particularly valuable in periods of tight credit. Indeed, we find a shift toward models receiving captive support when lenders report tightening their conditions for collateral. This is evident even among purchasers that use bank financing and therefore cannot be attributed simply to a pull-back in bank credit. Captive finance thus appears to have a positive spillover effect on equilibrium lending by other financial intermediaries, notably when credit is relatively scarce.

Our findings are related to both the literature on vendor financing as well as the literature on durable goods. Within the vendor financing literature, we add to a long list of motivations for firms to finance their own product. Our contribution is not to rule out all other motivations for captive finance, but rather to present an idea that is new to this literature, and importantly, one with distinct testable predictions. Most relevant to our work are the papers discussed above under the information asymmetry hypothesis that document a signaling role for trade credit in a market with adverse selection. We suggest a nuanced retelling of this story whereby, rather than signaling hidden information, manufacturers use financing to commit to hidden actions. Our paper also relates to earlier work by Biais and Gollier (1997), who first suggested that vendor financing can resolve information asymmetry about borrower risk and thereby generate positive spillovers by facilitating bank financing. We observe similar spillover effects driven by a commitment to high collateral resale value. Within the literature on durable goods, the idea that manufacturer leasing can solve Coase's time-inconsistency problem is as old as the problem itself. However, ours is the first paper to show that risky debt contracts offered by vendors can serve a similar role in theory and practice and to empirically test the role of vendor financing in solving Coase's famous conjecture.

The remainder of the paper is organized as follows. Section I provides institutional background on captive finance companies and develops testable hypotheses. Section II describes the data. Section III details the empirical results. Section IV concludes.

I. Background and Hypothesis Development

A. Institutional Background

A captive finance company is typically a wholly owned subsidiary of a manufacturer that provides retail and wholesale financing for the parent's products. Familiar examples include the finance subsidiaries of major automobile manufacturers (e.g., Toyota Financial Services, GM Financial, Ford Credit). Among heavy construction equipment manufacturers, the largest captive finance companies include Caterpillar Financial, John Deere Capital, Case-New Holland (CNH) Capital, Komatsu Financial, Kubota Credit, and Volvo Financial Services, which together held more than $100 billion in total finance receivables as of 2013.

While these companies actively provide short-term wholesale financing for dealers, the bulk of their assets consist of longer term secured loans made to retail customers. Lease financing is small relative to secured lending, constituting 18%, 8%, and 10% of the retail finance portfolios reported in the 2013 10-K's for Caterpillar, Deere, and Case-New Holland, respectively. This matches the characterization of contracts in our data, for which less than 10% of total contracts are flagged as leases. The construction finance industry skews more heavily toward secured lending than does the broader equipment finance industry, where leasing made up approximately 30% of retail finance portfolios from 2000 to 2009.[2]

The captive finance companies in our sample are funded largely by issuing long-term debt, which mostly consists of medium-term notes structured to match the maturity of the financing assets. It is also typical for captive finance companies to access commercial paper markets and to borrow directly from their parent companies. Of particular interest for the hypotheses tested in this paper, however, are the securitization practices of the captives. Loan sales or risk transfer by lenders could easily undo the effect of captive finance on manufacturer incentives to restrict production or their ability to signal product quality. Sutherland (2016), however, reports that securitization plays a minor role in this market, which is consistent with our reading of regulatory filings by large captives. As of 2013, the six largest captives had securitized 14% of their finance portfolios. Most of this is driven by CNH; excluding CNH, only 5% of financing assets were securitized. In all cases, securitized assets

[2] See Captive finance firms in a challenging economy, Equipment Leasing & Finance Foundation, 2009.

remain on balance sheet with significant retained interest, such that even CNH discloses its exposure to loan performance and collateral values in its 2013 10-K as follows: "An increase in customer credit risk may result in higher delinquencies and defaults, and a deterioration in collateral valuation may reduce our collateral recoveries, which could increase losses on our receivables and leases and adversely affect our financial position and results of operations." Similar disclosures are found in the annual reports of the other major captives as well. Hence, even with securitization, captive lenders appear to remain significantly exposed to the resale price risk of their collateral, consistent with security design preserving incentive compatibility.

Although the literature on captive finance has been limited to this point, earlier work suggests some predictable sources of variation in its use. For example, Bodnaruk, O'Brien, and Simonov (2016) show that captive finance subsidiaries are more prevalent among large firms, firms with high levels of market share, and firms in concentrated industries. Among producers for which we can identify the home country, we find that non-U.S. firms provide significantly less financing for their products. We also show that captive finance tends to skew toward riskier purchasers and varies based on both equipment type and equipment size (specifically, captive finance is considerably more prevalent among compact machinery). These facts inform many of the controls in our basic specifications. Finally, perhaps, not surprisingly, considerable variation in captive financing can be explained by a manufacturer's history of financing activities. We exploit this variation in Section III.D where we use the spin-off of a division from one manufacturer to another to generate variation in the level of captive financing for an otherwise unchanged product line.

B. Hypothesis Development

In this section, we explore potential mechanisms through which a manufacturer of durable goods can enhance its profits by offering financing for its products. In particular, we focus on the idea that, by providing financing, manufacturers can commit to or signal future product value, raising the willingness-to-pay of current-period customers. This idea is grounded in two closely related classes of theories, each with distinct testable predictions.

On the one hand, captive financing's potential role in signaling value might be naturally interpreted as a form of product quality guarantee. This idea plays heavily in the literature on trade credit. By way of example, Long, Malitz, and Ravid (1993) propose slow payment by buyers as a way to allow time for inspection of the underlying good, facilitating the separation of high- and low-quality producers. Lee and Stowe (1993) and Emery and Nayar (1998) also discuss mechanisms whereby trade credit provision serves to signal the underlying good's quality. In the context of longer term secured captive lending against durable equipment, we might naturally interpret quality as shorthand for long-term machine productivity, whereby low-quality machines cease to be productive due to either physical degradation or technological obsolescence over a shorter time horizon. A sufficient condition for captive finance to credibly signal that goods will retain their productivity is the threat that unproductive machines will be returned to the manufacturer. This might be achieved through leases or through secured lending contracts, provided that there is a threat of default when realized equipment values are low enough.

While this idea is compelling, it is also somewhat limiting. Captive financing may serve producers by allowing them to signal higher future values for their product due to ex-ante production choices (e.g., product quality), but it may also be driven by the need to commit to ex-post production choices that have an equal hand in determining future machine value.

In particular, we have in mind Coase's (1972) classic analysis of the time-inconsistency problem faced by a durable goods monopolist, whereby, absent a credible commitment to take actions that support product value in future periods, consumers' rational anticipation of excessive product depreciation erodes the manufacturer's rents today.[3] While Coase (1972) and subsequent authors point out that leasing products as opposed to selling them can serve as such a commitment device, this observation has not played a prominent role in our understanding of vendor financing to date. Below, we show that, to commit manufacturers to low ex-post depreciation, leasing contracts are not strictly required—both leases and loans funded by the manufacturer can achieve the same ends.

To fix ideas, below, we sketch out the simple intuition regarding how captive lending and leasing can solve the limited commitment problem of a durable goods manufacturer. The more formal presentation of the model, which is an extension of Bulow (1982), is provided in the Internet Appendix.[4]

Consider a two-period setting in which a durable goods producer faces a downward-sloping demand schedule for its product. The firm produces q_t machines in each period $t = 1, 2$ using a production technology with constant marginal cost. Machines do not physically depreciate between periods 1 and 2, except in the sense that they have only one period of usefulness remaining in period 2. The stock of machines at a given point in time thus includes current production plus any past periods' production.

In this setting, Bulow (1982) shows that a manufacturer that can commit to future production will choose to produce only in the first period. This maximizes total profits by providing the optimal stock of outstanding machines in each period. Restrictions on future production raise the purchase price of the good today enough to more than offset any potential profits that could have been earned through second-period sales. A manufacturer that lacks an effective

[3] Coase's (1972) analysis focuses on the manufacturer's production volume. However, the time-inconsistency problem is much more far-reaching, encompassing any future action that the firm might take that could affect the value of past customers' used goods. Previous theoretical work shows that the inability to commit leads durable goods producers to overinvest in R&D and to introduce new products too frequently (Waldman (1996)), to allow excess availability of used units (Waldman (1997)), and to monopolize maintenance markets (Borenstein, Mackie-Mason, and Netz (1995)), all of which undermine producer market power.

[4] The Internet Appendix is available in the online version of this article on the *Journal of Finance*'s website.

commitment mechanism, however, would respond to any residual demand by selling additional units in the second period. This time inconsistency in the producer's incentives prevents it from achieving first-best profits. Meanwhile, second-period production not only reduces first-period prices, but also leads to faster depreciation of the goods.[5] Recognizing this, any bank that finances the purchase would offer a relatively low LTV so as to avoid having borrowers with negative equity.

A large literature follows this basic point to show the various production or contracting solutions that can return the producer to first-best rents.[6] Probably, the most applicable of these proposed solutions to our empirical setting is that the manufacturer leases rather than sells its output. By leasing, the manufacturer retains legal ownership of its products and thus internalizes the future resale value of equipment, providing the necessary incentives to commit to the optimal production path.

Yet, in the model presented in the Internet Appendix, we show that it is not necessary for the manufacturer to retain ownership to align its incentives. The manufacturer can sell its output so long as it retains exposure to future prices on the downside, which it can achieve by providing secured debt financing for its customers. Returning to the simple two-period problem, suppose a manufacturer finances the sale of its own equipment in the first period. By offering low down payment/high LTV financing, the manufacturer ensures that first-period customers retain high loan balances in the second period. Then, if the manufacturer overproduces in the second period or takes any other ex-post action to depress second-period prices, first-period customers become underwater on their loans. In the simplest version of the model in which borrowers have no outside wealth or loans are without effective recourse, the secured loan contract acts exactly like a lease in forcing the manufacturer to internalize the full price effects of second-period production. However, strict assumptions on recourse or outside borrower wealth are not necessary—as long as lender profits are sensitive to the threat of borrower defaults and associated recoveries, lending contracts can satisfy the same role Coase initially proposed for leases.[7]

[5] That lack of commitment leads to higher depreciation rates is not a consequence of the two-period environment. Stokey (1981) studies the time-inconsistency problem in a discrete-time, infinite-horizon model, and Kahn (1986) analyzes a continuous-time setting with convex production costs. In both cases, without commitment, the manufacturer produces too much over time, driving prices down.

[6] Bulow (1982) and Desai and Purohit (1998) study leasing, Butz (1990) analyzes best-price provisions, in which the difference in price is refunded to any customers who paid a higher price for the same product, an alternative similar to the repurchase agreements proposed by Coase, Bulow (1986) shows that the durable goods monopolist can reduce its time-inconsistency problem by making goods with uneconomically short useful lives (planned obsolescence), Kahn (1986) shows that increasing marginal costs in the production function makes the problem less severe, and Karp and Perloff (1996) and Kutsoati and Zabojnik (2001) study the deliberate adoption of inferior production technology.

[7] For some firms, we can make back-of-the envelope calculations of manufacturers' sensitivity to collateral values. For example, Caterpillar's loan portfolio as of 2013, before reserves, was roughly 10 times net income. Meanwhile, economic losses on that loan portfolio will be equal to

There are two important differences between the manufacturer's solution with outside financing and that with captive financing. First, since captive finance creates incentives for restricted production in both periods, machines depreciate more slowly when they are financed by the manufacturer. Second, the manufacturer is able to offer a higher LTV when it finances its own machines. This is tied to the depreciation rate. Because the machines will be worth more in the future, the manufacturer can lend more without pushing the buyers underwater. In fact, since the threat of default is what provides commitment to the manufacturer, it is more accurate to say that the manufacturer *must* offer a higher LTV. If it were to offer the same high down payment/low LTV financing contract as we find under bank financing in the model, the manufacturer would not face any loan losses even under the higher level of depreciation observed with bank financing, limiting its commitment to keep prices high.[8]

Hence, the prediction that producers who finance their own sales can also support lower product depreciation rates can arise because financing gives sellers commitment to take ex-post actions in support of their older machines, or because financing offers a signal of quality in a market where buyers face asymmetric information about the productivity or longevity of their durable purchases. More generally, there may be a wide variety of mechanisms that could give rise to vendor financing being concentrated in high-quality machines. In Section III.A, we proceed by showing that, in practice, there is a strong relationship between realized depreciation on physical machinery and the identity of the financier, consistent with the hypotheses put forward above. In the sections that follow, we attempt to distinguish between the limited commitment hypothesis and those related to ex-ante quality.

Finally, while we have emphasized the role of secured lending above, given that leases and loans can achieve similar ends under both information asymmetry and limited commitment models, when we examine the data below, we focus more on who provides the financing and less on the form of the contract. Meanwhile, while leasing might appear to have an advantage over lending in the sense that, with leases, the manufacturer is exposed to residual values even without default (as described in the institutional details section above), secured lending turns out to be the dominant contractual form for captive finance companies in the construction industry. This might be consistent with the well-known problem associated with lease contracts when there is scope for abuse by the user of the underlying good. Bulow (1982) and Eisfeldt and Rampini (2009) both point out that leases suffer from the costs of separating ownership from control. Thus, benefits of leasing relative to lending may be offset by the higher monitoring costs when machine value is sensitive to the

the proportion of loans that ultimately stop paying $\times$ (1 – loan recovery rate). If we assume a 10% default rate (for example, based on Sutherland (2016)), then it is easy to show that depreciating old assets by 10% on average leads to a 10% reduction in earnings.

[8] This is true even in the version of the model in which recourse prevents some borrowers from strategically defaulting, since no borrowers default as long as they can sell their machine for more than the loan amount.

manner in which it is used. While the literature may benefit from further investigation of contract determination, doing so is beyond the scope of this paper.[9] Having said that, in Table I, we separate captive leasing from lending and find that leasing does appear to have the predicted relationship with depreciation, consistent with it being an effective mechanism when feasible.

II. Data

To test the hypotheses derived above, we focus attention on the market for heavy equipment used in construction and agriculture. We focus on heavy equipment for a number of related reasons. First, to match the interesting features of the model, we need a less-than-perfectly-competitive industry such that production and financing choices can interact meaningfully. While not monopolistic, the market for heavy machinery is controlled by a handful of large firms. By way of example, the most-purchased piece of equipment in our sample is a skid-steer loader—a small, four-wheeled machine with lift arms capable of pushing or lifting heavy material. In 2012, five manufacturers produced 93% of debt-financed skid steers in the United States. Thus, it seems plausible to presume that individual manufacturers have pricing power. The durable quality of goods is also central to our argument. Returning again to skid steers, the median used skid steer financed with secured credit in 2012 was eight years old, which is easily long enough for the value to be meaningfully impacted by ex-post producer actions.

Finally, we focus on heavy equipment because of its nature as capital investment (as opposed to a consumption good). Although, in theory, our hypotheses apply to consumer durables equally well, we think that some of the more interesting implications of our theoretical findings pertain to the potential link between captive finance and pledgeability and how this may impact borrowers facing credit constraints. To the extent that the relaxation of credit constraints is an important outcome of captive financing, any resulting impact on firm investment could have large spillover effects for the aggregate economy.

For our primary tests, we rely on two distinct sources of data. One, produced and sold by Equipment Data Associates (EDA), tracks financing statements filed by secured lenders for sales—new or used—of heavy equipment financed by secured debt (hereafter, the Uniform Commerical Code ("UCC") data, because financing statements are designated as the means of documenting liens under the uniform commercial code). The data represent the universe of complete filings with the exception of filings from the state of Nevada, which does not allow for bulk downloads. We use these financing statements to infer the extent to which financing is done by manufacturers or by competing banks, as our central predictions relate to how much financing support a manufacturer

[9] Other proposed solutions to the time-inconsistency problem, such as repurchase agreements, also suffer from the separation of ownership and control. Insofar as the terms offered by the manufacturer lead to the customer choosing to sell back the machine, the customer will not internalize its care. The same argument applies to best-price provisions/money-back guarantees.

lends to a given model. Although it is an open question as to whether financing statements are required for leases, the data and conversations with the data provider suggest that it is common practice to file financing statements for both loans and financing leases. As a result, we include both leases and loans in our analysis. We also use a limited sample of the data that contains information on the actual loan amount extended by the lender and an EDA-formulated estimate of the equipment value, which allows us to infer LTV, or percent down payment.

The data on financing statements 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. Lenders thus have strong incentives to promptly report the collateral they have lent against. Financing statements are publicly available, but EDA sells cleaned and formatted versions going back to 1990. An introduction to financing statements and the claim-staking process is available in Edgerton (2012), the first and only other paper we are aware of to use these data.

The second data set we exploit is produced by EquipmentWatch, a data provider that reports results from heavy equipment auctions going back to 1993. While not comprehensive, we have data on the sales/purchases of over one million pieces of equipment from the largest auctioneers of heavy equipment.[10] The machine-level observations include sales price as well as both auction and equipment information, such as age, condition, and make/model. The average estimate of equipment value from EDA and actual sales prices at auction are $89,455 and $30,750, respectively. The difference partially reflects the fact that, while auction sales include both cash and debt-financed sales, the EDA estimates only reflect sales financed by secured debt. Additionally, auctions are composed almost exclusively of used sales, while financing statements include new and used sales. For reference, Table IA.I in the Internet Appendix lists the most common machine types and manufacturers in the UCC data by observation count, while Table IA.II reports select summary statistics.

III. Results

A. Captive Finance and Resale Prices

Our central hypothesis, and thus the first testable implication we investigate, is that products that are financed by their manufacturers will have higher future resale values. After documenting the relationship between resale performance and financing, we turn to distinguishing the importance of financing's role in providing ex-post commitment to maintaining price levels from competing hypotheses about ex-ante machine quality.

[10] EquipmentWatch claims that it has 90% coverage of equipment auctions going back to 1990, notably excluding auctions run by IronPlanet.

Table I begins the analysis by comparing model-specific estimated depreciation rates in the used equipment market with the degree of financing support offered for each model. We estimate depreciation rates for each equipment model using the auction sample by regressing the log sales price on log machine age. Before running regressions for each equipment model, we remove year fixed effects, estimated over the entire sample, from both equipment age and price. Thus, time fixed effects are treated as constant across model-specific regressions. Formally, our measure of depreciation comes from the regression

$$\ln(\widetilde{AuctionPrice_{i,t}}) = \alpha_{\text{model}} + \delta_{\text{model}} \ln(1 + \widetilde{EquipmentAge_{i,t}}) + \epsilon_{i,t}, \qquad (1)$$

where δ_{model} is estimated separately for each model based on the sales of individual machines i at auctions in year t, and $\ln(\widetilde{AuctionPrice_{i,t}})$ and $\ln(1 + \widetilde{EquipmentAge_{i,t}})$ are demeaned by the average yearly log price and log (1+) machine age at auction. Age is calculated as the number of years between the original manufacture date and the date of resale for each machine being sold. The coefficient δ_{model} captures the model-specific depreciation rate. It should be interpreted as the percentage loss in value for a proportional increase in age.

With a measure of depreciation in hand, we can now project it on the level of captive financing support available for a given model. Specifically, the variable *ModelCaptiveSupport* is the percentage of new machines of a given model financed by a captive finance lender over the entire sample. (Note that we only observe transactions conditional on financing, so our measure of captive support does not take into account cash sales, for example). Our focus on captive support only over new machines allows us to isolate the effect of captive financing availability, rather than variation in new versus used sales, which is closely related to lender type. As a point of reference, for the average make and model, 37% of new machine sales/leases were financed by the manufacturer. To reduce noise, we limit attention to models for which we have 30 or more transactions in both the auction and the UCC data, which leaves us with 1,599 models. To isolate the effect of financing, we control for fine-level equipment-type fixed effects, as well as a set of 26 size dummy variables, where size is characterized by EDA based on important machine characteristics, often horsepower or weight.

Column (1) of Table I reports estimates from the model

$$-\delta_{\text{model}} = \alpha + \beta_1 ModelCaptiveSupport + \beta_{2\ldots k} Controls_{\text{model}} + \epsilon. \qquad (2)$$

We estimate a coefficient on *ModelCaptiveSupport* of -0.14, suggesting that moving from a fully bank-financed model to one that is completely financed by the manufacturer would predict a reduction in the machine's depreciation rate of 14 percentage points. Note that a 14 percentage point change in depreciation is equivalent to a move from the 50^{th} to the 80^{th} percentile of the depreciation distribution after conditioning on size and machine type, or equivalently, 22% of the mean depreciation rate. Figure 2 shows this graphically, plotting mean

Table I

Captive Finance and Resale Prices

The table documents the relationship between the resale value of heavy machinery and the extent of captive financing in the primary market. Depreciation rates are estimated for each make and model (conditional on having 30 or more resale observations) based on the regression: $\ln(\widetilde{AuctionPrice}_{i,t}) = \alpha_{\text{model year}} + \delta_{\text{model year}} \ln(1 + \widetilde{EquipmentAge}_{i,t}) + \epsilon_{i,t}$, where i indexes an individual machine and t is the year of the auction. Year fixed effects are estimated in the full auction sample and partialled out of age and price in a first-stage regression. Equipment age is the number of years between the original manufacture date and the date of resale. $-\delta_{\text{model}}$, the model-specific depreciation rate, captures the percentage loss in value for proportional increases in age. Columns (1) through (5) report regressions of the depreciation rate on the fraction of new machines that are financed by captive finance units for each model, along with controls for equipment type and size, $-\delta_{\text{model}} = \alpha + \beta_1 ModelCaptiveSupport + \beta_{2...k} Controls_{\text{model}} + \epsilon$. *ModelCaptiveSupport* is calculated by model from the UCC filing data and is included only for models that had 30 or more machines financed from 1990 to 2012. In columns (1) and (2), it includes both captive loans and leases; in columns (3) and (4), loan and lease support is considered separately; and in column (5), the separate measures are both included in the regression. Standard errors are clustered at the manufacturer level, are robust to heteroskedasticity, and are reported in parentheses. ***, **, and * indicate results significant at the 1%, 5%, and 10% level, respectively.

Depreciation Rate	(1)	(2)	(3)	(4)	(5)
Model Captive Support	−0.14***	−0.20***			
	(0.04)	(0.04)			
Model Captive Support (loans)			−0.20***		−0.18***
			(0.04)		(0.04)
Model Captive Support (leases)				−0.49**	−0.33*
				(0.23)	(0.18)
Manufacturer Fixed Effects	NO	YES	YES	YES	YES
Equipment-Type Fixed Effects	YES	YES	YES	YES	YES
Equipment Size Fixed Effects	YES	YES	YES	YES	YES
Observations	1,599	1,599	1,599	1,599	1,599
R^2	0.47	0.56	0.56	0.55	0.56

depreciation rates across levels of captive finance. While the relationship is flat for small amounts of captive financing, we can see that above some threshold amount (roughly 50% of machines), depreciation rates appear to be strongly inversely related to captive support.

A sensible response to the observed correlation between captive financing and resale performance is to look for alternative machine characteristics that might drive both who finances machines and how the machine holds its value. Note that the inclusion of machine type and size fixed effects appears to rule out omitted variables related to fixed physical features of machines or intended uses, say, of backhoes versus excavators. Instead, it seems more likely that plausible confounding variables are driven by manufacturer characteristics. Column (2) of Table I includes manufacturer fixed effects, testing for differentials in rates of product depreciation across models within a manufacturer. The coefficient on *ModelCaptiveSupport* is not statistically distinct from the results in column (1) without manufacturer fixed effects, suggesting that unobserved and

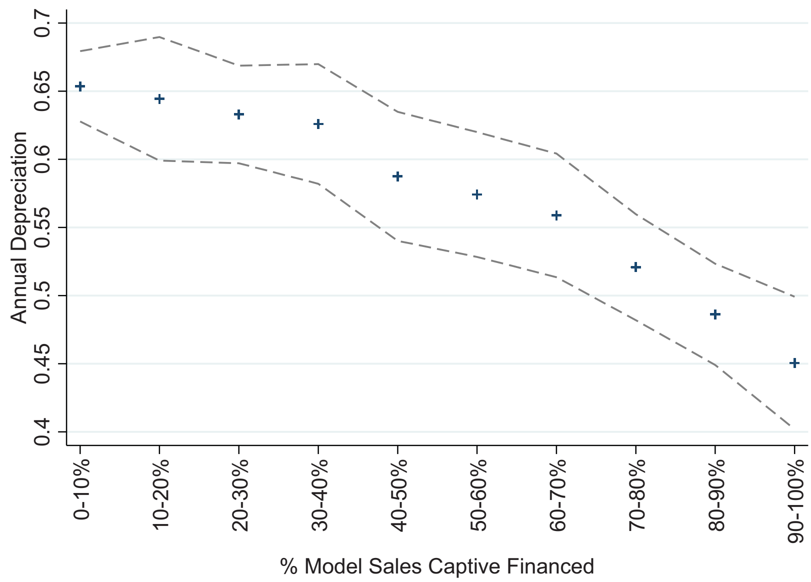

Figure 2. Resale depreciation and captive finance. The figure plots mean depreciation rates across different levels of captive finance. On the horizontal axis is the percentage of new sales of a given model that are financed by the manufacturer. On the vertical axis is the average depreciation for each bucket as estimated in equation (1), along with the associated 95% confidence intervals. (Color figure can be viewed at wileyonlinelibrary.com)

time-invariant manufacturer characteristics related to the level of captive financing do not explain the observed correlation.[11]

Notice that our measure of captive financing varies based on who the financier is, and not the form of the contract. While the machines in our sample are overwhelmingly debt-financed, in columns (3) and (4), we show that captive lease intensity is also strongly related to depreciation rates. However, including captive loan and lease measures side-by-side leaves captive leasing only marginally significant, perhaps due to the limited amount of variation in leasing support (for 50% of models, captive leasing is zero). Therefore, going forward, we continue to focus on the total measure of captive support that covers both leases and loans.

B. Limited Commitment versus Information Asymmetry Hypotheses

Absent further information, the results in Table I are open to a few distinct interpretations. As discussed in Section I.B, captive finance may help resolve time inconsistency for a durable goods producer with market power, committing

[11] Table IA.VI in the Internet Appendix shows that the specification survives manufacturer × time fixed effects with the time dimension fixed at the five-year level. At finer granularity, point estimates remain quantitatively similar but are statistically insignificant.

the manufacturer to support future resale values of today's machines. Alternatively, it may be the case that captive finance is concentrated in machines with high quality. Earlier work in the literature on vendor financing suggests, for example, that manufacturers might use financing to signal high quality in a market characterized by information asymmetry. We now turn our attention to differentiating between the predictions made by the competing models.

Critically, note that, under the two hypotheses, captive financing generates two distinct sources of variation in depreciation, which fortunately we can disentangle. On the one hand, under the hypotheses in which captive support is associated with machine quality, lower depreciation is driven by better machines that lose their productivity more slowly. Under limited commitment, however, captive-backed and bank-financed models remain equally productive over time, but depreciate differently due to supply effects or other ex-post manufacturer choices. To see how these effects manifest in terms of depreciation rates, consider the example of a 2002 vintage John Deere 210LE Tractor Loader. In 2003, the same machine will be a one-year-old 210LE, and we would measure its total depreciation as its new price in 2002 less its used price in 2003. We can also, however, decompose this total depreciation into two distinct components by considering the price of a new 2003 210LE (in 2003):

$$
\begin{aligned}
Dep_{02-03}(\text{'02 210LE}) &= P_{02}(\text{'02 210LE}) - P_{03}(\text{'02 210LE}) \\
&= \underbrace{(P_{02}(\text{'02 210LE}) - P_{03}(\text{'03 210LE}))}_{\text{“new price depreciation”}} \\
&\quad + \underbrace{(P_{03}(\text{'03 210LE}) - P_{03}(\text{'02 210LE}))}_{\text{“productivity-driven depreciation”}}.
\end{aligned}
$$

The first term, which we call "new price depreciation," captures the change in new machine prices from one year to the next. The second term captures the difference in price between a new and an old 210LE at a given point in time (2003 in the example). We call this component "productivity-driven depreciation" to capture the fact that this difference should be driven by the difference in the remaining productive lives of the new versus old machines. High-quality machines (those with long productive lives) should exhibit a shallow difference relative to lower quality machines.

Returning to our competing hypotheses, if captive finance signals high machine quality, then the results in Table I should be driven by lower productivity-driven depreciation among machines with strong captive support. This aspect of depreciation can be estimated in the cross section of machines of different ages but for sale at the same point in time (e.g., compare an '03 to an '02 model in 2003). In contrast, the ex-ante quality view offers no obvious prediction for new price depreciation, as it is not clear that machine quality tells us anything about how one vintage's new machine price should compare to the next.

Meanwhile, under limited commitment, we expect to see captive financing most directly affect new price depreciation. For example, if, absent captive

Table II

Captive Finance and Drivers of Depreciation

The table documents the relationship between the depreciation rates of heavy machinery and the extent of captive financing in the primary market. Depreciation rates are estimated in a variety of ways to isolate different drivers of depreciation. In column (1), the measure of depreciation captures the time-series change in new machine prices by including only machines less than two years old and in very good or excellent condition, and then regressing price on model age, defined as the number of years since the introduction of a given model. Column (2) isolates cross-sectional variation in model prices at a point in time driven by differences in machine productivity by adding auction year fixed effects to the depreciation regressions from Table I. Columns (3) and (4) use model-vintage-specific depreciation, controlling for physical condition as estimated in the regression in equation (5) in the text. The depreciation rates capture the percentage loss in value for proportional increases in age, holding condition fixed. These represent estimates of the price paths of "new-old-stock" machines. Each column thus reports regressions of the particular measure of depreciation on the fraction of new machines that are financed by captive finance units, along with controls for equipment type and size. *ModelCaptiveSupport* is calculated as in Table I, except for in columns (3) and (4), where it is calculated for each model $\times$ vintage in a backward-looking fashion. Standard errors are clustered at the manufacturer level (manufacturer and vintage year for columns (3) and (4)), are robust to heteroskedasticity, and are reported in parentheses. ***, **, and * indicate results significant at the 1%, 5%, and 10% level, respectively.

	New Price Depreciation	Productivity Driven Depreciation	New-Old-Stock Depreciation	
	(1)	(2)	(3)	(4)
Model Captive Support	−0.16***	−0.01	−0.12**	−0.20***
	(0.03)	(0.05)	(0.05)	(0.07)
Vintage Year Fixed Effects	NO	NO	YES	YES
Manufacturer Fixed Effects	YES	YES	NO	YES
Equipment-Type Fixed Effects	YES	YES	YES	YES
Equipment Size Fixed Effects	YES	YES	YES	YES
Observations	160	1,587	596	596
R^2	0.27	0.36	0.49	0.54

finance support, John Deere overproduces tractor loaders in 2003, this will push prices down for the new vintage of the same tractor-loader year-over-year. Yet, the same overproduction has ambiguous effects on productivity-driven depreciation, given that the excess supply in 2003 affects the 2003 value of both the '02 and the '03 210LE. Hence, examining the covariation in captive finance with the different components of depreciation may help disentangle the relative importance of the two mechanisms.

Columns (1) and (2) of Table II map captive finance to our best estimates of new price and productivity-driven depreciation above, beginning with new price depreciation in column (1). Although the auction data provide very little coverage of new machine sales, for a subsample of machines and auctions, EquipmentWatch codes the condition of individual machines as excellent, very good, good, fair, or poor based on a physical evaluation of the machines at the time of sale. In approximating new machines, we limit the sample to machines no more than two years old and in very good or excellent condition. Among these close-to-new machines, we then examine the price trend of each model based on years since model introduction to capture new price depreciation. That is, for each model for which we have at least 30 auction observations, we estimate

$$\ln(AuctionPrice_{i,t}) = \alpha_{\text{model}} + \delta_{\text{model}}\ln(1 + ModelAge_{i,t}) + \epsilon_{i,t}, \tag{3}$$

where model age is the machine vintage year less the minimum vintage year for that model in the sample. For the 160 models for which we can estimate new price depreciation, column (1) reports the specification reported in column (2) of Table I. The coefficient on model captive support of -0.16 is significant at the 1% level and strikingly consistent with the magnitude of earlier estimates from Table I. Recall that, while the limited commitment hypothesis makes clear predictions about new price depreciation, the information asymmetry view (and other models dependent on variation in quality) predicts covariation between captive finance and productivity-driven depreciation.

Column (2) examines productivity-driven depreciation. We isolate within-auction-year variation in price with respect to age for a given model by simply including auction year fixed effects in each depreciation regression. That is, the left-hand-side variable in column (2) is $-\delta$ from the following model-specific regression:[12]

$$\ln(AuctionPrice_{i,t}) = \alpha_{\text{model}} + \gamma_{\text{auctionyear}} + \delta_{\text{model}}\ln(1 + EquipmentAge_{i,t}) + \epsilon_{i,t}. \tag{4}$$

When we reestimate the basic fixed effects regression from Table I, but with the modified depreciation measure, the effect of captive support falls away. Moreover, the coefficient in column (2) is statistically different from that in column (2) of Table I at the 1% level. This would seem to call into question the importance of variation in quality as the driver of differences in depreciation.

Finally, note that our presentation of how machine quality might impact depreciation has emphasized the most obvious mechanism: better machines are more durable and hence lose value more slowly. However, the estimate of productivity-driven depreciation is more general than this as it captures *any* source of variation in machine longevity. A potentially important example might be the role of technological depreciation. If, for example, John Deere's '02 becomes technologically obsolete in 2003, this would be reflected in a price discount relative to the '03 model. Yet, we find no evidence of such effects related to model captive support.

Returning to the estimation of new price depreciation, a small caveat is in order. Ideally, to isolate the pure effects of new price depreciation, we would

[12] A clarifying point on the identification of depreciation rates here: because these regressions are at the model level, machines of different ages can trade within a given year, which allows for estimation of both age and time effects. This is in contrast to subsequent regressions at the model $\times$ vintage level in which age and time would be collinear.

compare year-over-year changes in identical brand-new machines. In practice, however, the example of P_{02}('02 210LE) $-$ P_{03}('03 210LE) will incidentally capture any change in design of new machines from '02 to '03. Meanwhile, neither class of theories makes clear predictions about how a model design will evolve year-to-year. Hence, an idealized measure of new price depreciation might be more accurately defined as "new-old-stock depreciation," that is, the change in price of hypothetically unused '02 210LEs from 2002 to 2003. This measure removes price effects due to changes in condition over time, and hence productivity, while preserving machine design from year to year.

While we do not directly observe "new-old-stock" machines, we can estimate this component of their depreciation by again exploiting information on machine condition. For the subsample of machines with condition information, we can estimate a separate depreciation path that holds condition constant—that is, we can estimate the change in price for a model over time imposing that its condition remains unchanged. Meanwhile, to hold model design fixed, we redefine the unit of observation to the make $\times$ model $\times$ vintage level, as opposed to pooling different vintages of a given model under a single make $\times$ model. We can thus estimate the depreciation of a new-old-stock '02 210LE over time.

Following the methodology in Table I, for each equipment model $\times$ vintage for which we have at least 30 observations in the auction data with condition information, we estimate $\delta_{\text{model},y}$ in the model below:

$$\ln(AuctionPrice_{i,t}) = \alpha_{\text{model},y} + \delta_{\text{model},y}\ln(1 + EquipmentAge_{i,t}) + \sum_{\text{cond}} \gamma_{\text{model},y} I(Cond_{i,t} = cond) + \epsilon_{i,t}. \quad (5)$$

We refer to $-\delta$ as new-old-stock depreciation. Columns (3) and (4) replicate the regressions in columns (1) and (2) of Table I, except with the unit of observation redefined at the make $\times$ model $\times$ vintage level and the left-hand-side variable replacing total depreciation with new-old-stock depreciation. While in earlier tests, we estimate the captive support for a given model over the entire sample, by operating at the model $\times$ vintage level, we can focus on the backward-looking history of captive finance for a make-model over the years prior to the current vintage year. Finally, by drilling down to the vintage year level, we can include year fixed effects based on the year in which a model was produced, removing any time-series covariation in financing and depreciation that might be behind Table I. Columns (3) and (4) show effect sizes that are unchanged from those in prior results, providing complementary evidence in an alternative sample and specification that differences in physical machine quality do not drive the earlier results.

Internet Appendix Table IA.IV provides a slightly different take on these regressions, estimating a measure of physical durability at the model level using auction data on condition and adding it to the regressions in columns (1) and (2) of Table I. Specifically, we define failure as a machine transitioning to fair or poor condition at auction and use survival analysis to estimate a survival function for each model. We then define durability as the estimated log median survival time for a given model. We describe the analysis in detail in the Internet Appendix. However, to summarize, we find that adding durability as a control strongly predicts dollar depreciation rates, but does not attenuate the coefficient on model captive support. Finally, consistent with these two results, model captive support is not a strong predictor of estimated durability.

In summary, we find no evidence that captive-financed machines are of better quality, either in terms of physical quality or due to otherwise protracted productivity. While we have emphasized models with information asymmetry as a natural alternative to the limited commitment view, the lack of variation in observed quality across captive-versus-bank-financed models weakens this interpretation. Meanwhile, the tests described below more closely tie our findings to a model of limited commitment.

C. Market Power

The motivation for examining captive finance as a response to the problem facing durable goods producers with market power was driven in part by the observation that captive financing is associated with large firms (see Mian and Smith (1992) and Bodnaruk, O'Brien, and Simonov (2016)). The persistence of the observed relationship between captive financing and resale values within manufacturer in Tables I and II, meanwhile, raises an interesting question: why would a manufacturer provide more financing to some models than others? Understanding captive finance as a commitment device for firms with market power suggests one potential answer: manufacturers do not need the commitment afforded by captive finance in markets where they have limited ability to set prices. That is, if a manufacturer's production level has no impact on price, then commitment to restrict production over time is not valuable. The limited commitment hypothesis can only explain the use of captive finance by firms with market power and predicts that the within-firm variation in *ModelCaptiveSupport* underlying Tables I and II should follow within-firm variation in product market power.

This prediction is consistent with the data. Figure 3 plots the use of captive finance across different models against the market concentration for the equipment type. The x-axis is the decile of either the Herfindahl index ("HHI") or a measure of concentration defined by the inverse number of active producers of a given machine type (e.g., skid-steer loader, mini-excavator, etc.) in a given year, while the y-axis presents the average model-year captive support within each decile. Consistent with the findings in Bodnaruk, O'Brien, and Simonov (2016), an active role for captive finance appears to manifest more prevalently in high-HHI industries and in industries with fewer producers.

Table III brings us to a similar, but more pronounced, conclusion. Column 1 regresses *ModelCaptiveSupport* on the natural log of a model's market share, along with controls for equipment type, size, and manufacturer fixed effects. Market share is estimated for new equipment sales within a given equipment type. It is calculated annually and averaged over the life of the model.

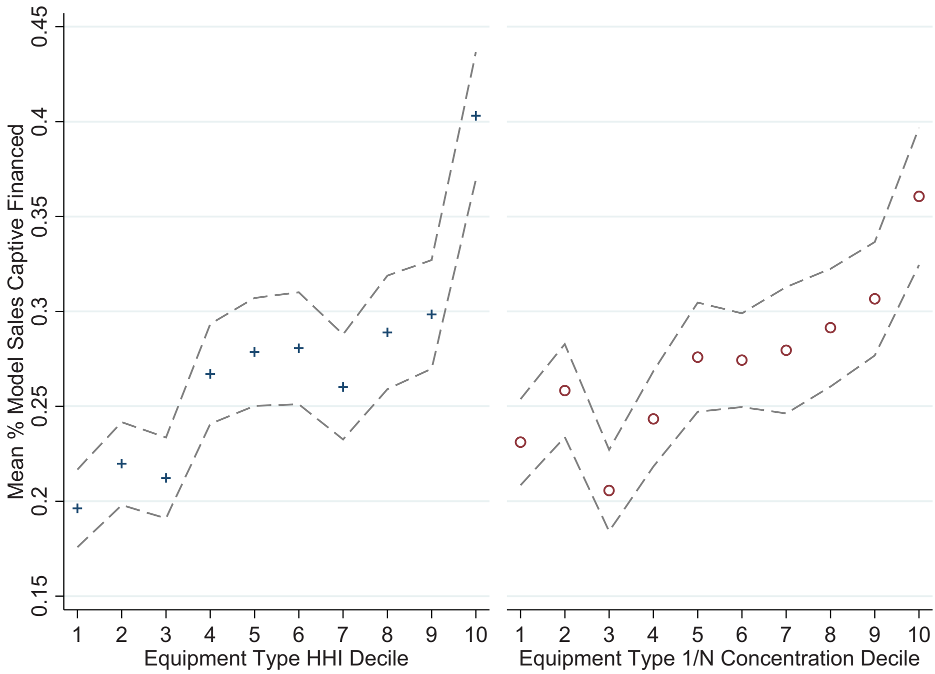

Figure 3. Captive finance intensity and market power. The figure plots the level of captive finance support received by an equipment model as a function of the concentration of the model's market. The vertical axis is the average percentage of new sales financed by the manufacturer, averaged over machine type × year observations, along with the associated 95% confidence intervals. The horizontal axis is the decile of either the Herfindahl index or a measure of concentration defined as the inverse number of active producers of a given machine type in a given year. (Color figure can be viewed at wileyonlinelibrary.com)

We find that, even within a given manufacturer, models receiving captive support are more likely to be models with substantial market share. Although earlier work suggests a relationship between firm size or market share and the use of captive finance, we are able to exploit machine-level data to show that this relationship holds within a manufacturer. This allows us to rule out explanations that would link market share and captive support indirectly through observed or unobserved time-invariant manufacturer characteristics.

A natural question that arises from the result above is whether manufacturers direct financing at models with market share, or whether financing that is directed at specific models causes high market share for the same models. Barrot (2016), for example, shows that larger firms may use trade credit provision as a competitive device to crowd out financially constrained competitors. To address this question, in column (2), we estimate market share based only on bank-financed sales. This helps us avoid capturing market share that is driven by captive financing, as opposed to captive financing that is plausibly driven by market share. The effect is slightly smaller, but still significant at 0.02.

Table III

Captive Finance and Market Power

Columns (1) and (2) estimate the link between market share for a particular model and the extent to which that model receives captive support. Market share is estimated for new equipment sales within a given equipment type. It is calculated annually and averaged over the life of the model. Market share estimates in column (1) are based on all UCC filings and in column (2) are based only on bank-financed sales to avoid capturing market share that is driven by aggressive captive financing terms. Columns (3) through (5) extend the regressions of Table I to include an interaction term with model-specific market share. *High Market Share* is a dummy variable equal to 1 if a model is above the median market share in the sample. Column (3) uses the broad measure of market share, whereas column (4) uses the share within the bank-financed universe. Column (5) includes as an interaction an alternative measure of market power based on the inverse number of active producers for each type of equipment. Sample size is somewhat larger than in Table I, where only models with more than 30 recorded sales are included in the analysis. Here, we include these models so as not to exclude models with low market share (the variable of interest). All regressions include manufacturer, equipment type, and equipment size fixed effects. Standard errors are clustered at the manufacturer level, are robust to heteroskedasticity, and are reported in parentheses. ***, **, and * indicate results significant at the 1%, 5%, and 10% level, respectively.

	Model Captive Support		Depreciation Rate		
	(1)	(2)	(3)	(4)	(5)
ln(Market Share)	0.05***	0.02***			
	(0.01)	(0.01)			
Model Captive Support (MCS)			−0.04	−0.05	−0.05
			(0.05)	(0.05)	(0.05)
MCS × High Market Share			−0.14***	−0.15***	
			(0.04)	(0.04)	
High Market Share			0.04	0.07***	
			(0.03)	(0.02)	
MCS × Market Concentration ($\frac{1}{N}$)					−0.63***
					(0.21)
Manufacturer Fixed Effects	YES	YES	YES	YES	YES
Equipment Type Fixed Effects	YES	YES	YES	YES	YES
Equipment Size Fixed Effects	YES	YES	YES	YES	YES
Observations	2,600	2,435	2,597	2,432	2,586
R^2	0.61	0.62	0.46	0.47	0.46

Columns (3) to (5) combine this result with the results from Table I to show that captive finance can only predict resale values when the manufacturer has market power. Here, we replicate the regression of depreciation rates on *ModelCaptiveSupport* and controls for equipment type, size, and manufacturer from Table I, but add an interaction with a dummy variable for models with above-median market share. In column (3), market share is estimated broadly. In column (4), it is limited to bank-financed sales. In each case, the interaction is negative and significant. For models with above-median market share within a given machine type, going from 0% to 100% captive finance of new sales reduces depreciation rates by 18 to 20 percentage points, versus a statistically insignificant reduction of 4 to 5 percentage points for models with below-median market share.

Because one might still worry that causal effects of captive financing on market share muddy the interpretation, column (5) zooms out and replaces market share with a market-wide estimate of concentration, specifically, the inverse of the number of firms producing a given equipment type. Similar to market share, it is calculated annually and averaged over the life of the model. Although market share is what matters—even in a concentrated industry, captive finance will be of limited commitment value for small players—we can think about this regression as using the number of firms in an industry almost as an instrument for market share. The findings are consistent with the idea that the relationship between depreciation and financing weakens in more competitive markets. Going from the 10^{th} to the 90^{th} percentile in one over the number of firms (moving from roughly 35 to 4 producers) shifts the sensitivity to *ModelCaptiveSupport* from -0.07 to -0.21.[13]

D. Evidence from Volvo's Acquisition of Ingersoll Rand Unit

Absent a large-scale natural experiment to generate random variation in captive financing across our entire sample, we have relied on mostly broad-sample correlation-based evidence to interpret the observed link between how firms finance their sales and the depreciation rates associated with their products. We now add to this evidence the results of a quasi-experiment affecting a set of machines that went from receiving no financing support from the manufacturer to substantial captive backing over a short period of time to examine their subsequent resale performance. While we do not argue that the change in financing was randomly assigned, the motivations for the change are at least readily understandable. Moreover, while financing patterns changed, the machines being produced and the means of servicing them seem to have been largely unchanged. This fact helps narrow the set of plausible interpretations of prior results.

[13] Although in Figure 3, above, we also demonstrate the correspondence between HHI and the use of captive finance, in the make-model level regressions, focusing on the number of producers has more natural predictions. As stated above, our sharpest predictions are with respect to market share. Hence, to the extent we substitute market share for an equipment-type-level measure of concentration, we want a measure that unambiguously affects the average firm's market share. The inverse number of active producers satisfies this role—if four firms produce and one leaves the market, the average firm's market share must increase. In contrast, note that HHI can be decomposed into two components—first, HHI is driven by $\frac{1}{N}$, and second, it is driven by a component capturing the variance of market shares (formally, $HHI = \frac{1}{N} + \sum(s_i - \bar{s})^2$, where s_i is firm i's market share and $\bar{s}$ is the mean market share). Unlike $\frac{1}{N}$, a shock to the variance of market shares has perfectly offsetting predictions for the average firm's market share (one firm's gain must be another firm's loss). Hence, any relevant variation in HHI must be driven by $\frac{1}{N}$. Meanwhile, as a secondary issue because subsequent tests examine quantity share as an outcome of interest, measures of concentration that do not directly depend on market share may be preferable. Therefore, in this test and those going forward, we focus on $\frac{1}{N}$ as our measure of concentration.

Specifically, we focus on the acquisition of Ingersoll Rand's road construction division by Volvo in 2007. The road construction unit was part of Ingersoll Rand's construction technology division. Though a small part of the total firm, generating less than 10% of operating income in 2006 (Ingersoll Rand annual report 2006), the division was a large part of the road construction market, with 25% market share as of 2004 measured using new units financed in the UCC data. The sale to Volvo was driven by a strategic realignment that redirected resources to other divisions, including the larger climate control and security divisions. The proceeds from the $1.3BN sale were used to fund acquisitions and a continued share buyback program. The sale does not appear to have been driven by distress, but rather strategic fit for the two companies.[14]

Two aspects of the sale are of interest. First, the acquisition gives sharp variation in captive financing support. While Ingersoll Rand was not historically active in financing, Volvo had a large preexisting consumer finance division that immediately began aggressively financing the formerly Ingersoll Rand machines. Second, for a long period following the acquisition, the affected machines were manufactured under the same designs and in the same plants as they had been when owned by Ingersoll Rand. As an example, the specifications for the most popular Ingersoll Rand roller (the DD-24) are listed in the Internet Appendix alongside the same key specifications for the Volvo DD-24 roller. A side-by-side comparison suggests that these two products are very nearly identical. Also included in the sale were Ingersoll Rand's service and maintenance facilities. Thus, when we study resale performance, neither physical characteristics of the machines nor service quality are likely to be material drivers of any changes in resale performance. In this way, the unit sale helps us isolate the hypothesized role for captive financing from potentially confounding characteristics of bank-financed versus manufacturer-financed machines.

Figure 4 documents the patterns of interest. Using the UCC data, we plot the market share of Volvo and Ingersoll Rand among affected machines within the road construction segment. In the two plots, we observe both the market share and the share of captive financing for Ingersoll Rand and later Volvo as active producers of road compaction equipment and road-paving equipment (the two broad segments of road construction equipment included in the sale). Road compaction equipment includes a broad range of machine types, from manually operated rammers to larger single-drum and tandem-drum vibratory compactors, all broadly designed to accomplish the goal of flattening surfaces on soil, gravel, or pavement. The spin-off, however, also included the sale of road-paving equipment, including tracked pavers, wheeled pavers, and road wideners. All told, 23 different equipment types were included in the sale, including 61 different affected models (those models that were produced by Ingersoll Rand/Volvo and that traded both before and after the spin-off).

[14] Reuters's announcement provided the following commentary on the sale from Volvo's perspective: "In terms of products this is right. These are things they don't have in their product line-up. In terms of the price, you always pay quite a lot for these types of assets since they have rather high margins" (Volvo to buy Ingersoll Rand Road unit for $1.3 BN, Reuters, 2/27/2007).

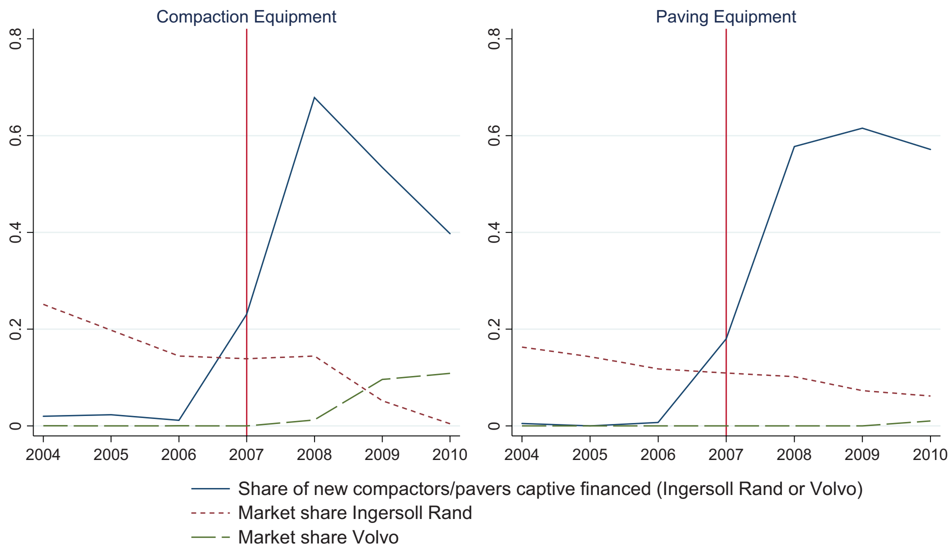

Figure 4. Ingersoll Rand sale of road construction equipment unit to Volvo. The figure plots the market share of new road construction equipment of Ingersoll Rand and Volvo (based on units financed in the UCC data) as well as the combined share of new machines that were financed by a captive. The left panel corresponds to compaction equipment and the right panel to paving equipment. (Color figure can be viewed at wileyonlinelibrary.com)

Meanwhile, these represent diverse classes of equipment, ranging in weight from 500 kg to 11.9 metric tons and in price from \$3,500 (the first percentile of transaction price within the auction data) to \$127,000 (the 99$^{\text{th}}$ percentile).

In the plots, with compaction equipment represented on the left and paving equipment on the right, notice that the acquisition by Volvo shows up in the data beginning in 2007 and 2008, as sales of Ingersoll Rand equipment gradually decline and are slowly replaced by Volvo-branded equipment. As of 2008, combined sales of Volvo/Ingersoll Rand compaction and road-paving equipment captured in the UCC data represented 14% of the total number of machines sold, second in market share only to Caterpillar. More important, however, is the fact that the transaction increased captive financing of affected Ingersoll Rand products from 0.91% in 2006 to 66% in 2008. Column (1) of Table IA.VIII in the Internet Appendix presents this chart in a make $\times$ model fixed effect regression, where we regress a dummy indicating whether a new compaction or paving machine was captive financed on a post-2007 dummy interacted with a dummy for formerly Ingersoll Rand machines (post-2007 Volvo machines), along with make $\times$ model and year fixed effects. Holding model-specific attributes fixed, the spin-off raised captive financing by 44%, an effect that is both economically and statistically significant at the 1% level.

How do we explain the large change in machine financing? As mentioned above, Volvo had an active financing arm that was useful in serving Volvo's largest business line (trucks and buses), which are naturally amenable to captive financing. Meanwhile, while we cannot say with certainty why Ingersoll

Rand was less active in captive finance, we suspect that this is also related to the company's broader business strategy. At the time of the divestiture, Ingersoll Rand's largest divisions were producing climate control equipment and refrigeration units for buses and refrigerated trailers, along with grocery-store-refrigerated displays. They later used cash from the division sale to expand this brand with the acquisition of Trane heating and cooling systems and services. Thus, the bulk of Ingersoll Rand's business was in products that, for practical reasons, would not appear to easily lend themselves to security interest, whether through leasing or loans. In sum, we think about the variation in captive financing as coming from some combination of historical persistence, fixed costs of establishing a lending unit, and the usefulness of having a lending arm across the producer's portfolio of products.

Using the divestiture and resulting change in machine financing as a source of variation, Table IV again tests for the relationship between machine depreciation and source of financing. Here, the estimation strategy approximates a triple difference-in-difference by estimating the effect of age on machine value for Ingersoll Rand machines before and after the acquisition of the business by Volvo. The difference in depreciation is then benchmarked against changes in depreciation observed for similar machines made by rival producers over the same time period.

Take the simplest presentation of the test described above. For the four subgroups (treatment, control, pre, and post), we run separate regressions of log price on log age and make × model × vintage fixed effects. In these tests, we are approximating earlier depreciation regressions, but pooling our estimates of depreciation rates across the four subgroups (instead of estimating the make-model-vintage-specific depreciation regressions) to economize on parameters.

The results of this simple exercise, as shown in Panel A of Table IV, are telling. For the control group—manufacturers of road construction equipment other than Ingersoll Rand or Volvo—the average depreciation rate captured by the slope on log age is 0.33 in the years before 2007 and 0.38 thereafter. That is, for the control group, depreciation rates are stable and not statistically distinct. In contrast, prior to 2007, Ingersoll Rand machines exhibited depreciation of 0.44. The difference relative to the control in the preperiod of 0.11 is perhaps consistent with the lack of captive financing capabilities. Yet, in the post-2007 period, once Volvo's captive financing arm is active, this number increases to 0.33 when applied to both old Ingersoll Rand and new Volvo machines, an improvement relative to the control of 0.16 (significant at the 5% level).

Panel B of Table IV extends these results to a more fully specified model in which we combine the four regressions into one and add various controls and combinations of fixed effects. The economic message, however, is largely unchanged. Formally, we estimate the regression

$$\begin{aligned}\ln(AuctionPrice) = {} & \beta_1 \ln(1 + MachineAge) + \beta_2 Post \times \ln(1 + MachineAge) \\ & + \beta_3 IR \times Post + \beta_4 IR \times \ln(1 + MachineAge) \\ & + \beta_5 IR \times Post \times \ln(1 + MachineAge) + \lambda Controls + \epsilon,\end{aligned}$$

Table IV

Ingersoll Rand Unit Sale and Resale Performance

The table estimates the impact of Ingersoll Rand's sale of its road construction equipment unit to Volvo and the related increase in captive financing that followed on the depreciation of machines sold at auction. The sample consists of all individual machine sales of road paving and compaction equipment in the auction data. *IR* is a dummy for machines made by Ingersoll Rand prior to 2007 and made by Volvo thereafter. *Post*2007 is a dummy for auction sales occurring in 2007 or after. Panel A reports depreciation regressions with make $\times$ model $\times$ year built fixed effects for each of the four groups defined by $\{Pre2007, Post2007\} \times \{Control, Treat\}$, where the control group is producers other than Ingersoll Rand or Volvo. Panel B includes all of these interactions in the same regression. The interaction of $Post2007 \times IR \times \ln(1 + MachineAge)$ gives the change in depreciation of formerly Ingersoll Rand-made machines after the acquisition, relative to similar machines over the same time period. Columns (1) and (2) use the full sample of road-paving and compaction equipment made between 2000 and 2013. Column (3) excludes machines produced by Volvo, limiting the treatment group to only the machines actually produced by Ingersoll Rand before 2007. Column (4) excludes the interactions with *MachineAge* to examine the level effect on prices captured in the coefficient on $Post2007 \times IR$. In Panel C, we divide the sample into low- and high-captive-propensity machine types based on the captive support provided for each machine type out-of-sample (for non-Ingersoll Rand/Volvo producers and before 2000) to focus on predetermined differences in expected treatment intensity. The sample is divided at the median level of captive propensity. Regressions supporting the first-stage effect of the acquisition on captive finance intensity are in Internet Appendix Table IA.VIII, while a regression documenting the parallel trend in machine prices is in Table IA.VII. Standard errors are in parentheses and are clustered at the level of the manufacturer. ***, **, and * indicate results significant at the 1%, 5%, and 10% level, respectively.

Panel A: Depreciation Rates

ln(MachinePrice)	Pre2007 × Control (1)	Post2007 × Control (2)	Pre2007 × IR (3)	Post2007 × IR (4)
ln(1+ MachineAge)	−0.33***	−0.38***	−0.44***	−0.33***
	(.04)	(.04)	(.06)	(.08)
Make × Model × Year Built FEs	YES	YES	YES	YES

Panel B: Change in Depreciation Rates and Price Levels

ln(MachinePrice)	(1)	(2)	Excluding Volvo-Made Machines (3)	(4)
ln(1+MachineAge)	−0.41***	0.09	0.06	−0.43***
	(0.03)	(0.07)	(0.07)	(0.02)
Post2007 × ln(1+MachineAge)	−0.02	0.03	0.01	
	(0.08)	(0.06)	(0.06)	
IR × ln(1+MachineAge)	−0.07***	−0.08*	−0.08*	
	(0.03)	(0.04)	(0.04)	
Post2007 × IR	−0.20*	−0.21**	−0.18*	0.06***
	(0.12)	(0.09)	(0.10)	(0.02)
Post2007 × IR × ln(1+MachineAge)	0.17**	0.17***	0.15**	
	(0.08)	(0.06)	(0.06)	

(Continued)

Table IV—*Continued*

Panel B: Change in Depreciation Rates and Price Levels

ln(MachinePrice)	(1)	(2)	Excluding Volvo-Made Machines (3)	(4)
Make × Model Fixed Effects	YES	NO	NO	YES
Make × Model × Year Built FEs	NO	YES	YES	NO
Year Fixed Effects	YES	YES	YES	YES
Condition Fixed Effects	YES	YES	YES	YES
Auctioneer Fixed Effects	YES	YES	YES	YES
Observations	14,368	12,606	11,184	14,368
R^2	0.42	0.42	0.46	0.42

R^2

Panel C: Change in Depreciation Rates by Captive Propensity

ln(MachinePrice)	Low-Captive-Propensity Machines (1)	High-Captive-Propensity Machines (2)
ln(1+MachineAge)	0.11**	0.04
	(0.05)	(0.12)
Post2007 × ln(1+MachineAge)	0.13	−0.01
	(0.09)	(0.11)
IR × ln(1+MachineAge)	−0.02	−0.20***
	(0.03)	(0.07)
Post2007 × IR	−0.04	−0.50**
	(0.07)	(0.20)
Post2007 × IR × ln(1+MachineAge)	0.04	0.37***
	(0.05)	(0.12)
Make × Model × Year Built FEs	YES	YES
Year Fixed Effects	YES	YES
Condition Fixed Effects	YES	YES
Auctioneer Fixed Effects	YES	YES
Observations	6,153	6,429
R^2	0.52	0.40

where *Post* is a dummy equal to one for machines sold at auctions in 2007, and thereafter, an *IR* is a dummy for machines produced by Ingersoll Rand prior to 2007 and Volvo during and after 2007. The coefficient on $\mathit{IR} \times \mathit{Post} \times \ln(1 + \mathit{MachineAge})$ indicates whether Ingersoll Rand machines depreciated differently postdivestiture relative to broader trends in machine depreciation over the pre- and postperiods (captured by $\mathit{Post} \times \mathrm{In}(1 + \mathit{MachineAge})$). Notice that *Post* is defined by the year of the auction and not the year the machine is produced. This is important because, unlike a depreciation effect driven by differences in how the machines were produced, which could hold only for machines produced post-2007, a commitment to higher resale values induced by Volvo's increased role in financing should also benefit machines produced prior to 2007. We can (and do) test this specific prediction by limiting the sample to machines produced prior to 2007, for which depreciation rates can be dictated only by ex-post producer behavior and not ex-ante design or build choices by Volvo that differed from Ingersoll Rand.

Given that our auction data run only to mid-2013, we limit the analysis to post-2000 auction data, roughly balancing the sample around the 2007 hand over. We also limit the age of the machines at auction to those less than seven years old, given we only observe secondary sales of Volvo compactors/pavers up to this age. Finally, we control for auctioneer fixed effects and for the reported condition of the machine at auction when available (condition is classified as excellent, very good, good, fair, poor, new, or unknown), although, for the majority of machines, the condition is unknown.

The results are reported in Panel B of Table IV. Column (1) includes make-model fixed effects. Columns (2) and (3) include make × model × vintage fixed effects. Finally, column (3) excludes machines manufactured under Volvo ownership, that is, it reports how machines made by Ingersoll Rand depreciated before and after Volvo ownership relative to the control group.

In each case, the evidence is consistent with the prediction that the increase in captive financing post-2007 changed how machines maintained their value over time. The coefficient on $IR \times Post \times \ln(1 + EquipmentAge)$ ranges from 0.15 to 0.17 and suggests that, following the acquisition by Volvo, machine depreciation slowed by 15 to 17 percentage points relative to the pre-acquisition period. The coefficient on $\ln(1 + EquipmentAge)$ in column (1) suggests a baseline 41% elasticity of machine price with respect to age for non-Ingersoll Rand/non-Volvo machines before 2007.[15] Again, the improvement in depreciation is relative to the change in depreciation of non-Ingersoll Rand/Volvo machines over the same time period (although this benchmarking is not critical, as Panel A suggests that there is no evidence that depreciation rates of road construction equipment changed for the control group from 2000 to 2006 versus 2007 to 2013).

While our predictions and tests focus primarily on the role of financing in preserving machine value over time, we also expect the level effect on machine value to be positive, as commitment to support prices in the future leads to higher prices today. Column (4) shows this directly, bypassing the interaction between age and postdivestiture and focusing on $Post2007 \times IR$. The coefficient of 0.06 suggests that, controlling for age, model, and condition, the price of the average affected machine increased by 6% following the divestiture. Meanwhile, Table IA.VII in the Internet Appendix estimates the year fixed effects for affected machines in the years leading up to and following the treatment and demonstrates an immediate increase in average machine prices suggested in column (4), with no evidence of a preexisting trend.

[15] The coefficient on age is harder to interpret in columns (2) and (3), which include both model × vintage fixed effects and auction year dummies, which combined are collinear with age and nearly collinear with In*(1+Machine Age)*.

Because the experiment relies on a single acquisition that simultaneously affects an entire class of machines, there is scope for concern that we have missed a confounding aspect of the transaction that drives the observed variation in machine prices but has nothing to do with the change in financing. Ideally, we would have an additional control group within the set of affected machines—models that were part of the spin-off but that were not impacted by the change in financing. Of course, if we were to simply compare the newly financed machines to models for which Volvo, ex-post, chose to withhold financing, we would introduce the risk that Volvo chose not to support some models based on private information.

In the absence of an instrument for treatment intensity within the set of acquired makes and models, we turn instead to predetermined machine characteristics that, out of sample, are associated with a propensity for captive finance. Specifically, for any machine type involved in the acquisition, we estimate the percentage of sales or leases that were captive-financed in the pre-2000 era, excluding any Ingersoll Rand or Volvo manufactured machines; we refer to this measure as *MachineCaptivePropensity*. Our conjecture is that if some machine types lend themselves more naturally to captive versus bank financing, then, given the newly found capacity to offer captive financing for old product lines, Volvo will increase its financing share relatively more for these machines (that is, relative to the more typically bank-financed machines). This, in turn, generates predetermined variation in the expected intensity of treatment and allows us to compare outcomes based on their exposure to captive finance. This test is similar in spirit to that in Rajan and Zingales (1998), who estimate financial dependence by industry in the United States and apply the resulting industry classifications to non-U.S. firms to learn about the causal effects of financial development.

The first-stage regression plays out as we might expect. As shown in column (2) of Table IA.VIII in the Internet Appendix, the increase in captive financing for formerly Ingersoll Rand machines is significantly more pronounced for machines that, out of sample and for unrelated producers, also tended toward captive financing. In Panel C of Table IV, we use *MachineCaptivePropensity* as a source of variation in the realized growth in financing around the spin-off. We rerun the specification from column (2) of Panel B, this time splitting the sample around the median *MachineCaptivePropensity*. A comparison of the relative depreciation rates captured by the interaction on $IR \times Post \times \ln(1 + EquipmentAge)$ suggests that the financing aspect of the acquisition is indeed critical to the observed price effects. While we might have predicted some impact on depreciation among the less affected machines, there is no obvious change in depreciation rates evident in column (1). Although these machines did experience growth in captive financing (Volvo increased financing by 29 percentage points for low-captive-propensity machines), the magnitude of the financing effect of the spin-off is considerably smaller than for the machines captured in column (2) (for which Volvo increased financing by 50 percentage points). Meanwhile, the depreciation effect for the more affected machines in column (2) is both significantly larger than that in column (1) (with a p-value of 0.01) and economically larger than the population-averaged result in column (2) of Panel B. So, while we cannot rule out unknown nonfinancial effects of the merger driving the changing depreciation rates, such effects would also need to covary with the same machine characteristics that drive our ex-ante predictions regarding the size of the financing effect.[16]

E. Evidence on the Quantity Mechanism

The evidence so far has focused on distinguishing among different hypotheses about the role of captive finance companies by examining patterns in equipment prices. We now turn our attention to potential mechanisms by examining the production choices of the manufacturers in our sample. While we are sympathetic to wide-ranging behaviors that could affect vintage machine prices under the umbrella of the limited commitment problem—again, previous authors have suggested that aftermarket support, new product development, and scrap rates are all ex-post decisions that firms might like to commit to ex-ante (Borenstein, Mackie-Mason, and Netz (1995), Waldman (1996), Waldman (1997))—given the emphasis on production quantities in earlier work and the clarity of predictions associated with this mechanism, we would be remiss in not examining it. Our findings suggest a strong link between manufacturers' history of captive financing for a given equipment type and attenuated production growth.

Before proceeding, it is worth noting that our measurement of quantities is imperfect. Information on sales volume by model and/or equipment type is closely guarded by producers. We can therefore measure quantities only from the UCC data. However, because this measure of quantities depends on machines being financed and reported in the UCC data, we cannot distinguish between hypotheses in which captive finance drives future quantities produced from alternative hypotheses under which high captive share precedes low total financing volume across both captives and banks.

With this caveat in mind, we test the hypothesis that captive financing inhibits production by examining the future sales of new equipment (as observed in the UCC data) as a function of the history of captive finance support. This analysis is run at the make $\times$ equipment type $\times$ size $\times$ vintage year level. Defining the unit of observation this way allows us to avoid problems in measuring quantities that would arise from the introduction of new models to replace old models. Our measure of captive finance is backward-looking as in columns (3) and (4) of Table II, so that *ModelCaptiveSupport* measures the proportion of new machines of a given type and size that were captive-financed prior to the current vintage year. As in prior tables, we require more than 30 sales to estimate the measure of captive support. The outcome of interest is average sales

[16] Table IA.IX in the Internet Appendix reports results of a similar exercise in which we replace *MachineCaptivePropensity* with the combined market share of Volvo and Ingersoll Rand prior to the spin-off. We find comparable effects. The use of market share as a sorting variable is motivated by the results in Section III.C, which show that market power is a key determinant of *MachineCaptivePropensity*.

Table V

Captive Finance and Quantities

The table estimates the relationship between the history of captive financing support for equipment and subsequent production volumes of that equipment. The analysis is at the make × equipment type × size × vintage year level to avoid problems in measuring production quantities at the model level that would arise from the introduction of new models to replace old ones. Quantities are measured based on new machines financed in the UCC data. Average future production for one, three, and five years is normalized by current-period production: $\frac{1}{N}\sum_{n=1}^{N} q_{t+n}/q_t$. *ModelCaptiveSupport* is backward-looking and measures the proportion of new machines of a given type and size that were financed by the manufacturer prior to the current vintage year. Standard errors are clustered at the manufacturer level, are robust to heteroskedasticity, and are reported in parentheses. ***, **, and * indicate results significant at the 1%, 5%, and 10% level, respectively.

N-Year Average Future Sales/Current Sales	$N=1$ (1)	$N=3$ (2)	$N=5$ (3)
Model Captive Support	−0.06	−0.21**	−0.34***
	(0.06)	(0.10)	(0.11)
Year Fixed Effects	YES	YES	YES
Manufacturer Fixed Effects	YES	YES	YES
Equipment Type Fixed Effects	YES	YES	YES
Equipment Size Fixed Effects	YES	YES	YES
Observations	22,414	22,414	22,414
R^2	0.05	0.12	0.13

of new machines over the next one-, three-, and five-year periods, relative to current-period quantities. An observation in year t is conditional on positive quantities in the current and lagged years, but does not require future quantities. Finally, we include fixed effects for the manufacturer, equipment type, size, and year.

Column (1) of Table V shows a negative but insignificant relationship between one-year production growth and a history of financing. But over the longer three-year and five-year periods, an effect is evident. Three-year average sales scaled by lagged sales drops by 0.21, moving from full bank to full captive financing, relative to a mean of 1.07. Similarly, five-year average sales scaled by lagged sales drops by 0.34, relative to a mean of 1.05. Interpreted through the lens of limited commitment, captive finance would appear to lessen the temptation to overproduce in future periods at the expense of current- and past-period buyers.

F. Captive Finance and Pledgeability

We now turn our attention to the effect that captive finance has on the equilibrium lending behavior of other financial intermediaries. In particular, the lower depreciation rates made possible by captive finance should imply that even traditional lenders can offer higher LTVs on machines with strong captive support. While simply observing more aggressive lending standards by captives (discussed below) would perhaps not be surprising, the prediction that

Table VI

Captive Finance and Pledgeability

The table estimates the relationship between the down payment required for individual machine buyers and captive financing support at the model level. *Downpayment* is measured as $\frac{Price-LienAmount}{Price}$, where *Price* is an EDA-provided estimate of machine value and *LienAmount* is the loan or lease amount as reported for a subsample of the UCC data. *ModelCaptiveSupport* is the proportion of new machines of a given model that are financed by the manufacturer over the entire sample, conditional on having at least 30 transactions financed. Column (1) includes all leases and loans. Column (2) includes only bank-financed transactions to avoid capturing differences in terms offered by captives versus banks. Column (3) includes an interaction with a measure of market power based on the inverse number of active producers for each equipment type. Column (4) replaces the *ModelCaptiveSupport* measured over the entire sample with a backward-looking measure of *ModelCaptiveSupport*. Standard errors are clustered at the manufacturer and year level, are robust to heteroskedasticity, and are reported in parentheses. ***, **, and * indicate results significant at the 1%, 5%, and 10% level, respectively.

Down Payment	All Transactions (1)	Bank Transactions (2)	All Transactions (3)	All Transactions (4)
Model Captive Support (MCS)	−0.16***	−0.14***	−0.10***	
	(0.03)	(0.05)	(0.04)	
MCS × Market Concentration ($\frac{1}{N}$)			−0.64***	
			(0.19)	
Market Concentration ($\frac{1}{N}$)			0.55***	
			(0.14)	
Model Captive Support History				−0.09***
				(0.03)
Year Fixed Effects	YES	YES	YES	YES
Manufacturer Fixed Effects	YES	YES	YES	YES
Borrower Controls (State, Industry FEs)	YES	YES	YES	YES
Machine Controls (Type FEs, Size FEs, ln(age))	YES	YES	YES	YES
Sale/Lease Dummy	YES	YES	YES	YES
Observations	54,401	23,179	52,307	41,884
R^2	0.20	0.21	0.21	0.19

banks will lend more on machines that receive large amounts of captive finance suggests a broader importance for how machines are financed.

We test this prediction in Table VI by using a subset of financing statements for which the bank or captive reports the lien amount on their UCC filing. Combining this amount with an EDA-provided estimate of purchase price based on machine value at that point in time, we calculate the variable $Downpayment = \frac{Price-LienAmount}{Price}$. Of interest is the effect of captive financing on predicted down payment amounts, controlling for machine characteristics as well as borrower characteristics. While borrower characteristics are limited, we observe the borrower's state and industry and include dummy variables for each (industry dummies are at the two-digit SIC code level). For each machine, we can control for equipment manufacturer, type, size, and age, all of which may plausibly impact both the required down payment and the lender of choice. Among the transactions for which we can calculate down payment, a small minority (6.5%) are characterized as leases in the UCC filing. Given that our predictions should hold across loans and leases, we leave both transaction types in the data and add a control for the contract type.

Finally, and most importantly, we limit the analysis to bank-financed transactions. While Benmelech, Meisenzahl, and Ramcharan (2017) suggest an important role for captives in providing credit directly, we are interested in the indirect effects of captive financing through machine collateral requirements. To isolate these effects, it may be important to set aside transactions for which captives had a direct role and instead assess how captive lending interacts with noncaptive lenders' assessment of collateral.

Table VI reports the results. In column (1), we look at bank- and captive-financed transactions. We find that the relationship between captive financing support and down payments is large and significant, controlling for year, machine size, age, type, and manufacturer, as well as borrower state and industry fixed effects. A model without captive support requires a down payment (as a fraction of value) that is 16 percentage points larger than a machine that is otherwise always financed by the captive. This effect is large relative to the mean *Downpayment* of 22% in our sample. With average machine values of $89,455, this implies an additional $14,313 down payment required for machines receiving no captive support (relative to fully captive-financed models). Column (2) isolates bank-financed transactions and reports a nearly identical coefficient. In other words, captive financing raises LTVs even on transactions in which the buyer financed at a bank, indicating that the coefficient in column (1) is not simply capturing differences in terms offered by captive lenders. Consistent with earlier tests, we show in column (3) that the relationship between model captive support and down payment is significantly stronger in concentrated industries (as measured by the inverse number of producers), where manufacturers are more likely to be able to affect prices. Finally, column (4) repeats the specification in column (1) but replaces the pooled *ModelCaptiveSupport* with the backward-looking version used in columns (3) and (4) of Table II. Although we lose observations based on the requirement that captive support be estimated with more than 30 observations, we find a similar sign and significance.

These results suggest a positive spillover effect of captive finance. While the commitment to higher resale values appears to serve as a rent-seeking device, the resulting lower required down payments/higher pledgeability of machines that have received captive financing support may be of value when financing frictions, and thus the shadow value of pledgeable equipment, are high.[17]

To test this possibility, and to provide additional support for the argument that captive finance may help companies commit to production paths that foster greater pledgeability, we look to the revealed preference for makes and models that receive strong captive support during periods of credit tightening by banks.

[17] Benmelech and Bergman (2009) show that pledgeability in the airline industry is most valuable during industry downturns, when rationing is likely to be greatest.

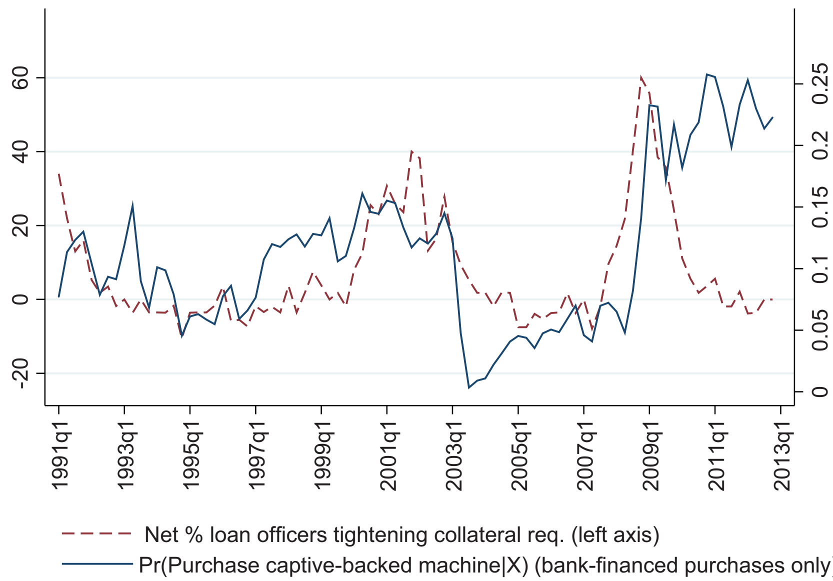

Figure 5. Machine choice and credit tightness. The figure plots the time series of the proportion of new bank-financed purchases of models with high captive support (above-median value captive financing percentage) on the right-hand axis. We compare this to the net percentage of loan officers that reported tightening collateral requirements on the left-hand axis. (Color figure can be viewed at wileyonlinelibrary.com)

Our prediction is that borrowers facing rising shadow costs of internal capital will choose machines with greater pledgeability—machines that have received captive financing support from their makers. Because we would like to avoid documenting possible substitution effects of bank financing being replaced by captive financing during periods of tight credit, we again limit our attention to the machine choice of borrowers financing their purchases with banks.

Figure 5 gives a taste of our findings. The figure plots the probability a given new machine purchase when financed by a bank will be of a make and model that received strong captive finance support over the entire sample period (defined as when the fraction of total machines financed by the manufacturer is more than the median across all models), controlling for equipment type and size.[18] This series (the solid line) is plotted against a dashed line representing a survey-based measure of banks' demand for pledgeable assets taken from the senior loan officer survey performed quarterly by the Federal Reserve Board of Governors. The survey asks loan officers whether they have tightened or loosened collateral requirements for small businesses. The Fed then reports the net percentage that reports tightening (percentage tightening minus percentage loosening). We find an apparent correlation between the two time series that is

[18] Specifically, the figure plots the time fixed effects from a regression of machine choice (captive supported machine or not) on quarter, equipment type, and size.

driven by large changes during low-frequency boom and bust periods, but also in the quarterly changes. In periods of tight credit, the demand for machines with captive finance support increases, even among bank-financed purchases.

Table VII reduces the graph in Figure 5 into a regression of an individual purchaser's machine choice on financing conditions, this time allowing for new and used transactions, as well as controls for machine age, type, and size. Given the concern that the recent credit crunches may have disproportionately affected industries that use machines that receive more captive support, we include both two-digit SIC industry and state fixed effects for machine buyers. The left-hand-side variable captures the consumer's choice, within an equipment type, of a captive-backed versus traditionally bank-financed model. Captive-backed models are those for which the model's captive finance support is greater than the median for that equipment type. Model captive support is estimated over the entire sample for models with more than 30 observations.

Column (1) reports the basic finding from Figure 5 that buyer preference for machines receiving above-median captive support increases during periods of credit tightness across the entire sample. The measure of credit tightness is normalized to have zero mean and unit standard deviation, such that a coefficient of 0.02 suggests that a one-standard-deviation increase in tightness is associated with a 2% higher probability of a consumer choosing a captive-backed model. The immediate concern, of course, is that this effect may be driven by greater availability of captive financing during periods of tight credit. To rule this possibility out, we focus on the subset of bank-financed transactions as we did in column (2) of Table VI. If the preference for captive-backed machines is driven by availability of captive financing, it should not affect buyers who choose to finance at the bank (if anything, we might expect the sample of bank transactions to be skewed away from captive-backed models). The effect, however, is unchanged when we focus on bank-financed transactions, showing a positive association between machine choice and aggregate conditions.

Columns (3) and (4) explore the robustness of the finding. Column (3) demonstrates that, consistent with prior results, the effects are stronger in more concentrated segments of the market. In column (4), we identify captive-backed models using only the backward-looking measure of financing used in Table II. That is, for each equipment model, we measure the percentage of all lagged annual transactions that were captive financed. We then define a captive-backed model as being above the median with respect to that measure. As before, we require 30 or more past transactions to estimate the percent of captive financing, which leads to some shrinkage in sample size. The results, however, are largely unchanged.

Of course, periods of credit tightness covary closely with other business cycle measures. As a result, it may be reasonable to interpret this pattern as a preference for captive-financed machines in downturns generally and not necessarily as evidence of a direct link to credit frictions. Moreover, we are sensitive to the fact that, while the time-series results appear statistically significant under our most conservative standard error estimates, we only have data over a few credit cycles.

Table VII

Machine Choice and Pledgeability in the Time Series

The table estimates the relationship between the yearly changes in collateral requirements reported by senior loan officers and the machine choice of bank-financed buyers. The left-hand-side variable is a dummy for whether the consumer chose a captive-backed model, defined as a model that received above-median captive support within its equipment type. As in earlier tables, model captive support is estimated over the life of the model for those models that have at least 30 transactions, except in column (4), where it is backward-looking. Collateral tightening reflects the net percentage of loan officers responding to the Senior Loan Officer Survey reporting tighter collateral requirements on commercial loans to small- and medium-sized firms during the year prior to the purchase. It is demeaned and given unit standard deviation for ease of interpretation. Borrower controls include state and industry fixed effects. Machine controls include machine-type fixed effects, size fixed effects, and the log of machine age. Column (1) includes all sales and leases. Column (2) limits the sample to bank-financed sales and leases to rule out the effect being driven by greater availability of captive finance during downturns. Column (3) adds an interaction with a measure of market power based on the inverse number of active producers within each equipment type. Column (4) replaces the left-hand-side variable with a dummy indicating whether the model chosen was above the median within its equipment type with respect to a backward-looking measure of captive finance support. Standard errors are clustered at the manufacturer and year level, are robust to heteroskedasticity, and are reported in parentheses. ***, **, and * indicate results significant at the 1%, 5%, and 10% level, respectively.

	Captive Support ≥ Median			Capt. History ≥ Median
Captive Backed Model Chosen	All Transactions (1)	Bank Transactions (2)	All Transactions (3)	All Transactions (4)
Collateral tightening (CT)	0.02***	0.02***	0.01	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
CT × Market Concentration ($\frac{1}{N}$)			0.14***	
			(0.01)	
Market Concentration ($\frac{1}{N}$)			−0.87*	
			(0.42)	
Borrower Controls	YES	YES	YES	YES
Machine Controls	YES	YES	YES	YES
Sale/Lease Dummy	YES	YES	YES	YES
Observations	2,835,511	1,150,262	2,824,264	1,993,691
R^2	0.08	0.06	0.08	0.20

IV. Discussion

In this paper, we motivate and document evidence of a strong correlation between use of captive financing and resale price performance for capital goods. The evidence is consistent with captive finance helping to solve the famous time-inconsistency problem introduced by Coase (1972). By financing their own output, manufacturers can commit to ex-post actions that support future machine prices. We further find that captive finance has spillover effects on the equilibrium lending behavior of other financial intermediaries. Strongly captive-backed equipment models support higher LTVs, even for individual machines that are financed by banks, and are favored by borrowers when access to funding is constrained. Thus, it may be reasonable to think about captive finance as a costly hedge, whereby the cost of restricted supply and the associated manufacturer rents afford the benefit of relaxed credit constraints on capital investment during periods of tight credit.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.