ASSET SPECIFICITY OF NONFINANCIAL FIRMS*

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We develop a new data set to study asset specificity among nonfinancial firms. Our data cover the liquidation values of each category of assets on firms' balance sheets and provides information across major industries. First, we find that nonfinancial firms have high asset specificity. For example, the liquidation value of fixed assets is 35% of the net book value in the average industry. Second, we analyze the determinants of asset specificity and document that assets' physical attributes (e.g., mobility, durability, and customization) play a crucial role. Third, we investigate several implications. Consistent with theories of investment irreversibility, high asset specificity is associated with less disinvestment and stronger effects of uncertainty on investment activities. We also find that the increasing prevalence of intangible assets has not significantly reduced firms' liquidation values. *JEL Codes:* E22, G31.

I. Introduction

Asset specificity is a hallmark of business operations in practice and a foundation of prominent theories in economics. When assets are specific to a given use, their liquidation values are limited; correspondingly, investment is irreversible. Such irreversibility can affect investment dynamics (Pindyck 1991; Bertola and Caballero 1994; Abel and Eberly 1996; Ottonello 2021) and magnify the impact of uncertainty (Bloom 2009). Low liquidation values can also influence organizational structures

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(Williamson 1981; Grossman and Hart 1986) and financial contracts (Shleifer and Vishny 1992; Hart and Moore 1994).

Although asset specificity is important to many economic theories, empirical research has faced a major challenge of measurement. There is a lack of data that directly captures the degree of asset specificity across different industries. Accordingly, some previous studies examine transaction prices of particular assets such as aircraft. Others rely on indirect proxies to cover more industries. One common proxy is tangibility (i.e., fixed assets over total assets), but this variable reflects the quantity rather than the specificity of fixed assets.[1] Given the scarcity of data, models have also used a wide range of parameter values for the degree of asset specificity.

In this article, we build a new data set that directly measures the liquidation values of the main categories of assets on firms' balance sheets (fixed asset, inventory, etc.) across all major industries. We quantify the degree of asset specificity using the liquidation value relative to the replacement cost, henceforth the liquidation recovery rate. This variable corresponds to parameters regarding asset specificity in a number of models, including the degree of investment irreversibility in Bloom (2009) and the per unit liquidation value of capital in Kiyotaki and Moore (1997).[2] We then investigate the determinants and the implications of asset specificity.

We hand collect data on the liquidation recovery rates of firms' assets using systematic disclosures of this information in U.S. Chapter 11 bankruptcy filings between 2000 and 2018. Specifically, firms in Chapter 11 continue to operate, but they are also required by law to report the estimated value of their assets if they

1. Studies of particular assets include Ramey and Shapiro (2001) for aerospace manufacturing equipment; Pulvino (1998), Gavazza (2011), and Franks et al. (2022) for aircraft; Campello, Kankanhalli, and Kim (2021) for ships; and Benmelech, Garmaise, and Moskowitz (2005) and Demirci, Gurun, and Yönder (2020) for commercial real estate. Studies using indirect proxies include Rajan and Zingales (1995), Almeida and Campello (2007), Gulen and Ion (2016), and Kim and Kung (2017), among others. Indeed, some work associated having more fixed assets (higher tangibility) with higher redeployability, whereas others associated it with greater sunk costs and lower redeployability.

2. Alternatively, one might define asset specificity as the value in alternative use relative to the value in current use. However, most firms have multiple types of assets, and the value in current use associated with each type of asset is difficult to assess. To the extent that the value in current use is often higher than the replacement cost (i.e., Tobin's Q is larger than 1), this alternative ratio could be lower.

were to be liquidated (over six months to a year). This reporting covers all of firms' assets on their balance sheets and provides detailed assessments for each balance sheet category, such as property, plant, and equipment (PPE) and inventory. These liquidation value estimates commonly derive from specialist appraisers who perform on-site examinations and simulate live liquidations; they also align with available auction results as we discuss later. The liquidation values reflect proceeds from reallocating standalone and separable assets (not combined with human or organizational capital), similar to the common formulation in models.[3] For each asset category, we compute the average liquidation recovery rate in a two-digit SIC industry to reduce noise and provide a data set that can be applied more broadly based on firms' industries.

We find that firms have high asset specificity on average, but the variations across industries are sizable. At the industry level, the liquidation recovery rate for PPE is 35% on average (with a standard deviation of 13%), and it ranges from over 60% for transportation services to less than 10% for personal services. The value for inventory is 44% on average (with a standard deviation of 17%), and it ranges from almost 90% for auto dealers to less than 20% for restaurants. For the firm as a whole, the total liquidation value (including fixed assets, working capital, cash, etc.) is estimated to average around 45% of total book assets, for firms in the Chapter 11 sample and those in Compustat (we calculate a Compustat firm's liquidation value by combining the industry-level liquidation recovery rate and the stock of each type of asset). A firm's total liquidation value is also typically less than its going-concern value (i.e., value of an operating business): the latter is twice as large even for the median Chapter 11 firm.

We perform extensive checks about the informativeness and generalizability of the data. We verify that the liquidation value estimates in our data are consistent with market-based transactions when such data are available. Specifically, the liquidation recovery rates are similar to auction results that cover equipment in aerospace manufacturing (Ramey and Shapiro 2001) and

3. If firms transfer discrete assets together with human and organizational capital, then the value would be akin to the value under current use (the going-concern value) rather than the liquidation value (Kiyotaki and Moore 1997). The going-concern value is typically much higher than the liquidation value. Accordingly, it is important for bankruptcy laws to preserve viable firms as operating businesses instead of liquidating them (Djankov et al. 2008; Kermani and Ma 2022b).

construction (Murfin and Pratt 2019). Total liquidation values in our data are also comparable to total proceeds in Chapter 7 liquidations.[4] We then verify that although the liquidation recovery rate data is most comprehensive for Chapter 11 firms, it is relevant for firms overall. For instance, our data are in line with lenders' liquidation value benchmarks for nonfinancial firms in general (e.g., 30% liquidation recovery rate for industrial PPE). We also impute the average recovery rate from PPE sales among Compustat firms, which aligns with the average PPE liquidation recovery rate in our data. Furthermore, as we show next, the liquidation recovery rates are shaped by the physical attributes of assets in an industry, which we measure among all firms in each industry using separate data sources. Finally, our data perform well in explaining investment decisions, financial policies, and organizational structures of firms in general as we show in the rest of this article and in Kermani and Ma (2022b).

After assembling the data set, we analyze the determinants of liquidation recovery rates. We document the importance of physical attributes in shaping the degree of asset specificity across different industries. For fixed assets in an industry, we measure three physical attributes: (i) mobility, using an asset's transportation costs (e.g., from producers to purchasers); (ii) customization, using the amount of design costs in producing an asset; and (iii) durability (as reallocation takes time), using depreciation rates. We construct these measures by collecting detailed information on the composition of fixed assets in an industry from the fixed asset tables of the Bureau of Economic Analysis (BEA), as well as the attributes of these assets (e.g., transportation cost and design intensity) from the BEA's input-output tables. We show that an industry's PPE liquidation recovery rate is lower when its assets are harder to transport, more customized, or less durable. Indeed, these three measures can account for nearly 40% of the cross-industry variations in PPE liquidation recovery rates. Moreover, our results indicate that if PPE had no transportation cost, no customization, and no depreciation, the liquidation recovery rate would be around 100%. In other words, low liquidation values of

4. Unfortunately Chapter 7 cases offer much less additional information which makes it difficult to calculate the liquidation recovery rate for each type of asset. Moreover, assets foreclosed by lenders or abandoned by the trustee are not included in the total Chapter 7 liquidation proceeds and require additional imputation (Bris, Welch, and Zhu 2006).

production assets depend crucially on their specificity in location, usage, and time span. Our findings resonate with the propositions of Williamson and, to our knowledge, present the first direct evidence of the physical foundations of asset specificity across industries.

We then study how economic conditions affect the variations of liquidation values over time. Consistent with Shleifer and Vishny (1992), liquidation values are higher under better industry conditions. In terms of magnitude, when industry sales growth is 10 percentage points higher, liquidation recovery rates increase by 1.5 percentage points on average. We find similar magnitudes using a large sample of construction equipment auctions. Accordingly, variations in economic conditions do not easily change the overall picture of high asset specificity among nonfinancial firms or offset the large differences across industries.

Asset specificity has a wide range of implications, and we focus on two main topics. We start with the classic issue of investment irreversibility (Pindyck 1991; Caballero 1999; Bloom 2014). We show that when PPE has lower liquidation values, firms indeed disinvest less and sell fewer fixed assets. We demonstrate that investment in PPE is more negatively affected by uncertainty when PPE liquidation values are lower, while inventory investment is more negatively affected when inventory liquidation values are lower. For both PPE and inventory, the estimated sensitivity becomes zero if their respective liquidation recovery rate is 100%: the investment response to uncertainty is absent if assets are fully generic. Finally, consistent with the insights of Guiso and Parigi (1999), high uncertainty (the second moment) not only reduces the level of investment but also dampens the responsiveness of investment to firm performance (the first moment), especially when liquidation values are low. Overall, the data show a high degree of alignment with theoretical predictions, both qualitatively and quantitatively, and offer direct evidence that asset specificity is fundamental for disinvestment frictions and the effect of uncertainty.

After analyzing traditional forms of investment, we shed new light on the economics of intangible capital, which is an important question for understanding the modern economy (Corrado, Hulten, and Sichel 2009; Eisfeldt and Papanikolaou 2013; Crouzet and Eberly 2019; De Ridder 2021). Intangibles consist of assets without physical presence, some of which are identifiable and separable (e.g., software, patents, usage rights), whereas others cannot exist independently from the firm (e.g., organizational capital). A major concern in the literature is that intangibles may decrease firms' liquidation values and tighten borrowing constraints (Giglio and Severo 2012; Haskel and Westlake 2018; Caggese and Pérez-Orive 2022; Falato et al. forthcoming). We find that the rise of intangibles has not led to a significant reduction in firms' liquidation values, since physical assets such as PPE are already highly specific and separable intangibles can generate liquidation values as well. Overall, the aggregate liquidation value among Compustat firms (relative to their book value or market value) in 2016 is similar to that in 1990, even though the amount of intangibles increased substantially over this period (e.g., intangibles rose from 6% of firms' book assets to 26%). What, then, is different about intangibles? Although intangibles may not be distinct along the dimension of asset specificity, they can be more scalable (because intangibles are nonphysical, they are not bound by a given location and could be nonrival in a firm). This aspect (and other changes in the production process) could be more important for future research on the implications of rising intangibles, whereas changes in firms' liquidation values may not be a critical issue.

Finally, we briefly discuss several additional implications of asset specificity, including productivity dispersion, price rigidity, and the boundaries of the firm. It is also natural to ask how asset specificity affects firms' debt contracts, which we study in a companion paper (Kermani and Ma 2022b). We find that liquidation values have a significant positive effect on total borrowing for small firms and firms with negative earnings, but not for large firms and firms with positive earnings (which primarily borrow on the basis of their cash flows rather than liquidation values). Meanwhile, liquidation values do affect debt composition and the intensity of creditor monitoring.

We end with a comparison of our data with parameter values that macro-finance models use for the degree of investment irreversibility or the liquidation value of physical capital. Some models produce high estimates of PPE liquidation recovery rates that are close to one (Cooper and Haltiwanger 2006; Lanteri 2018), while others find lower estimates between 10% and 50% (Evans and Jovanovic 1989; Catherine et al. 2022). The wide dispersion of model parameters also suggests that direct empirical evidence could be useful. We hope that our micro data can facilitate modeling analyses and help models incorporate the substantial variations in asset specificity across industries.

Our work makes three main contributions. First, we provide direct measurement of the liquidation value of assets across different balance sheet categories and industries. This new data set facilitates analyses beyond a particular type of asset (e.g., aircraft), and offers concrete information with clear units relative to indirect proxies. Second, we study the foundations of asset specificity. We document the role of assets' physical attributes (mobility, durability, customization) and the impact of industry conditions. Third, we leverage the granular nature of the data to illuminate leading implications of asset specificity. The physical attributes of assets we measure also allow us to show the physical foundations of these economic effects.

The rest of the article is organized as follows. Section II explains the data collection and presents basic statistics. Section III studies the determinants of asset specificity. Section IV investigates the implications of asset specificity. Section V summarizes the comparison with model parameters. Section VI concludes.

II. Data and Basic Statistics

This section describes our data on asset specificity of nonfinancial firms and our checks of its reliability.[5] We collect data on the liquidation recovery rate, namely, the liquidation value as a fraction of the net book value (cost net of depreciation), for major asset categories across industries. The liquidation value estimates represent proceeds from a typical orderly liquidation process that reallocates assets to alternative users (on a largely standalone basis without human or organizational capital). High asset specificity by definition means limited values in alternative use, and correspondingly low liquidation recovery rates. In Online Appendix 3, we build on the models of Gavazza (2011) and Bernstein, Colonnelli, and Iverson (2019) to illustrate that liquidation values are lower when assets are specific to a given location (high transportation cost), a given set of users (high customization), or a given time period (high depreciation). In Section III, we empirically examine the determinants of the liquidation recovery

5. We focus on nonfarm nonfinancial firms because the assets of financial institutions (e.g., securities and loans) and agriculture (e.g., farm lands) are rather distinct. According to the BEA fixed asset tables, nonfinancial industries account for around 90% of fixed assets and almost the entirety of intellectual property assets.

rates and document that these asset attributes play a key role.

The liquidation recovery rates in our data normalize assets' liquidation values using replacement costs, similar to the normalization in Ramey and Shapiro (2001); an alternative approach is to normalize liquidation values using asset values in current use. Our normalization is driven by three considerations. First, for each type of asset, the net book value is directly reported in our data, whereas the value in current use is difficult to assess (given that most firms have multiple types of assets). Second, the ratio of liquidation value to cost is largely determined by the inherent attributes of assets used in an industry (as we further verify in Section III), so it can be more reliably generalized to firms in the same industry. The ratio of liquidation value to value in current use is more firm specific because the denominator (value in current use) can depend on a particular firm's efficiency and managerial quality. Third, liquidation values relative to costs are widely used in models (where the key issue is how much of the investment cost can be recovered by the liquidation value); we discuss these models in more detail in Section V. Nonetheless, for a firm as a whole, we present a comparison of the total liquidation value relative to the value as an operating business in Section II.D. Finally, the liquidation recovery rate for each type of asset is different from the default recovery rate of debt (e.g., in Moody's data). We do not use the default recovery rate of debt to measure asset specificity because it depends on a firm's financial structure, the form of default resolution (reorganization or liquidation), and the administrative costs of resolution, so it does not directly reflect the value of a particular type of asset (see Kermani and Ma 2022b for analyses of the default recovery rate of debt).

II.A. Data Collection

A key challenge for measuring the degree of asset specificity among nonfinancial firms is the sparsity of data. For instance, secondary-market transactions are mainly available for a few relatively standardized assets, but difficult to obtain for many types of assets. To overcome this obstacle, we hand collect comprehensive reports covering all of the assets that firms own, which come from the liquidation analysis performed in Chapter 11 corporate reorganizations. In particular, firms in Chapter 11 continue to operate, but they are also required by law to assess the value of their assets if they were to be liquidated. This liquidation analysis presents the orderly liquidation value, which considers a scenario where a firm would cease operations and liquidate all of its assets over six months to a year. The orderly liquidation value is different from the forced liquidation value, which refers to forced sales in a short period of time (e.g., two months). The liquidation value estimates commonly derive from appraisals performed by asset liquidation and valuation specialists, who conduct field exams and simulate live liquidations to form the assessments. These appraisal companies are also the main liquidators of real assets, which gives them extensive knowledge of the liquidation process. In addition, they are responsible for assessing liquidation values for lenders who lend against particular assets (e.g., equipment, inventory); there is a similar process to appraise the assets' liquidation values and lenders then set borrowing limits accordingly (Udell 2004).

We begin with a list of U.S. public companies that emerged from Chapter 11 using New Generation Research (NGR)'s BankruptcyData. We use cases filed between 2000 (the start of electronic court filings) and 2018 and retrieve their liquidation analyses from Public Access to Court Electronic Records (PACER) and NGR.[6] The liquidation analysis typically includes a summary table with the net book value, liquidation value, and liquidation recovery rate (liquidation value as a fraction of net book value) for each main category of asset (e.g., PPE, inventory, receivable) and for the firm as a whole, along with notes that explain the sources and assumptions of the estimates. Table I shows two examples of the summary tables, from Lyondell Chemical and Sorenson Communications. Online Appendix 2 shows the detailed information behind the summary table for Lyondell Chemical, which includes the procedure for the estimates and plant-level appraisals for Lyondell's PPE. We use the midpoint estimate of the liquidation value in the summary table and the average of high and low estimates when the midpoint is not available. In other applications of the liquidation analysis data, Alderson and Betker (1995) and Dou et al. (2021) analyze the estimated total liquidation value of the firm as a whole to examine financial

6. The liquidation analysis is part of the disclosure statement associated with the Chapter 11 plan. When a case has multiple disclosure statements, we use the earliest version. If the liquidation analysis is not available in the first disclosure statement, we use the latest one.

TABLE I

LIQUIDATION ANALYSIS EXAMPLES

(Millions $)	Net book value	Low	High	Midpoint
Panel A: Lyondell Chemical				
Cash & equivalents & short-term investments	238.1	238.1	238.1	238.1
Trade accounts receivable	1,248.1	748.9	873.7	811.3
Other receivables	268.1	8.4	57.0	32.7
Intercompany receivables	30,474.1	0.0	0.0	0.0
Inventory	1,872.5	1,295.9	1,511.0	1,403.5
Prepaids and other current assets	305.4	0.0	0.0	0.0
Property, plant, and equipment, net	9,366.5	1,577.4	1,577.4	1,577.4
Investments and long-term receivables	27.5	0.2	1.8	1.0
Intercompany investments	43,823.1	336.1	373.1	354.6
Intangible assets, net	1,254.1	427.6	427.6	427.6
Insurance proceeds	0.0	0.0	229.6	114.8
Other long-term assets	72.2	61.6	63.6	62.6
Gross proceeds	88,949.4	4,694.2	5,352.9	5,023.5
Costs associated with liquidation:				
Payroll/overhead		(93.9)	(107.1)	(100.5)
Liquidation costs of PP&E		(157.7)	(157.7)	(157.7)
Chapter 7 trustee fees		(140.8)	(160.6)	(150.7)
Chapter 7 professional fees		(70.4)	(80.3)	(75.4)
Net estimated proceeds before EAI assets		4,231.3	4,847.2	4,539.2

TABLE I

CONTINUED

	Unaudited balances ($)	Estimated asset recovery (%)		Estimated recovery ($)	
($ in 000s)	Jan. 31, 2014	Low	High	Low	High
Panel B: Sorenson Communications					
Cash & cash equivalents	94,956	100	100	94,596	94,596
Accounts receivable	138,727	75	100	104,046	138,727
Prepaid and other current assets	8,351	5	10	418	835
Property, plant, and equipment, net	72,584	6	12	4,389	8,779
Goodwill, net	214,900	0	0	–	–
Intangible assets	98,765	17	50	16,348	49,043
Other assets, miscellaneous	16,901	0	3	–	550
Income from wind-down operations	–			–	30,276
Total assets and gross proceeds	644,824	34	50	219,796	322,805

Notes. This table shows two examples of the liquidation analysis summary tables. Panel A comes from Lyondell Chemical (case number 09-10023); the intercompany categories will drop out when the main entities shown here are consolidated with additional entities, so we do not use the intercompany categories. Panel B comes from Sorenson Communications (case number 14-10454).

structures following reorganization and bankruptcy frictions, respectively.

We have been able to retrieve liquidation analysis summary tables for about 400 cases covering nearly 50 two-digit nonfinancial SIC codes. We did not find information for all cases for two main reasons, both of which are more common among smaller companies. First, for 356 cases the liquidation analysis document cannot be found in the PACER system (e.g., local courts did not upload the document to PACER). Second, for 105 cases the liquidation analysis does not provide detailed information on the liquidation recovery rate for assets in each financial statement category (e.g., they only report the estimated total liquidation value of the firm without any breakdown or information of the book value). Online Appendix Table 1 lists the number of cases for each industry. We have fewer observations for industries where public firms are rare, such as construction contractors and building material retailing (fewer than 10–20 firms in Compustat). We have many observations for large industries, such as business services and chemicals. We performed detailed analyses to verify the informativeness of this data in the rest of the article.

We rely on public companies for the main data set because information is considerably harder to obtain for private companies. For instance, most bankruptcy filings do not contain an industry classification of the company. For public firms, NGR has assembled background company information including SIC codes, which we checked by hand using industry codes reported in SEC registration. For private firms, it is difficult to find reliable industry classification just based on company name in the bankruptcy filing. Furthermore, it is also more common that we cannot find the liquidation analysis document in PACER. However, we do collect additional data using the list of “Large Private Filings” compiled by NGR, where NGR cleaned the filing data and collected SIC codes. Using this list, we can obtain detailed information on the liquidation recovery rates for another 104 cases (filed between 2000 and 2018). The results are similar. For the industry-average liquidation recovery rate of fixed assets, for instance, the main data set and the expanded data set have a correlation of 0.94; the correlation is 0.97 for the industry-average liquidation recovery rate of inventory.

The liquidation analysis data has several advantages. First, it covers all of the assets firms own, rather than only assets with secondary-market trading data or those that have been chosen to be sold (Berger, Ofek, and Swary 1996; Pulvino 1998). Second, it reports not only liquidation values in dollar amounts but also liquidation recovery rates, which are important for constructing measures that can apply at the industry level and for making comparisons across industries or asset types. Third, the data have a standardized format for firms across different industries and a convenient level of aggregation corresponding to each financial statement category, so they can be directly matched with firm outcomes in standard financial reports (e.g., it is straightforward to study how the liquidation recovery rates of PPE affect investment in PPE). Finally, relative to indirect proxies of asset specificity, our data provide a uniform metric with a clear unit, which is important for interpreting empirical results (e.g., when the liquidation recovery rate is 0% versus 100%) and connecting to models.

We note two considerations related to liquidations. First, the liquidation values we report do not subtract overhead costs of the liquidation process, which are 5% to 10% of total liquidation value. In other words, our data represents gross liquidation values (i.e., proceeds from asset sales) rather than net liquidation values (i.e., sales proceeds minus overhead costs). Second, by design, the sale of assets in a liquidation is not optional. If instead asset sales are discretionary, then the observed sale prices can be affected by not only the intrinsic specificity of an asset but also the reservation price of the seller (e.g., the value in current use) and other strategic considerations; they are also less likely to cover specialized assets. The model in Online Appendix 3 verifies that discretionary sales are much less likely to occur when asset specificity is high. Overall, the orderly liquidation value captured by our data offers a simple and consistent metric across different types of assets and industries.

Finally, our data cover assets owned by firms. Firms may also use assets through operating leases, which were not reported on their balance sheets before 2019.[7] We focus on owned assets in this article because real decisions like investment expenditures capture spending on owned assets. In addition, owned assets appear to dominate in quantity in most industries. Specifically, starting in

7. In addition to operating leases, firms can also have capital leases (also known as finance leases), which are treated differently from operating leases. Assets under capital lease and capital lease liabilities are recorded on firms' balance sheets. The quantity of capital leased is small. For instance, in Compustat, the median (mean) ratio of capital lease to total book assets is 0 (0.007). About 10% of firm-years report a ratio greater than 0.01.

2019, a new accounting rule (Accounting Standards Update 842) requires firms to report the capitalized value of leased (right-of-use) assets and corresponding operating lease liabilities. Based on the new disclosure, the median ratio of leased assets to owned assets is about 3.5% among Compustat firms (the interquartile range is 1.6% to 8.1%). The prevalence of operating leases also appears to be largely an industry attribute, and industry fixed effects (e.g., two-digit SIC) account for about 40% of R^2 in the variation of the ratio of leased assets to owned assets. The ratio of leased to owned assets is particularly high for certain retail industries (median above 20% for restaurants, department stores, apparel, furniture, hardware, and food stores), modest for airlines and cinemas (median around 10%),[8] and low (median well below 10%) for most other industries (see Online Appendix Table 21 for more detail).

II.B. Asset-Level Liquidation Values

For each type of asset, we construct the measure of asset specificity by calculating the average liquidation recovery rate in an industry. The main asset categories include fixed assets (PPE), inventory, receivables, and book intangibles, which correspond to the standard categories in financial statements. Averaging by industry has two functions. First, the industry-level data can be extended to firms in each industry more broadly, and industry features such as the physical attributes of assets used in production play an important role in shaping the liquidation recovery rates as we show in Section III.A. Second, the industry-level measures can reduce idiosyncratic noise at the individual case level. We discuss further checks about measurement noise in Section II.C. Our baseline analyses use industry-average liquidation recovery rates for two-digit SIC codes for two reasons. First, the physical attributes of assets that we analyze in Section III are measured at the two-digit SIC code level (we construct key physical attributes for each industry in BEA fixed asset tables, which largely map into two-digit SIC codes). Second, our main liquidation recovery rate data set relies on public firms due to data availability as explained earlier; many three-digit SIC codes have few public firms to begin

8. For instance, the 2019 Annual Report of Southwest Airlines shows that it has a total of 747 aircraft, of which 625 are owned and 122 are leased.

with.[9] We perform robustness checks using industry-average liquidation recovery rates for three-digit SIC codes in Section IV.

Table II lists the industry-level liquidation recovery rates and Table III, Panel A presents summary statistics. For PPE, the average liquidation recovery rate is 35% (i.e., the liquidation value of PPE is on average 35% of net book value). The value is higher in industries with more generic PPE, such as transportation services (62%). It is lower for manufacturing (two-digit SIC between 20 and 39), where facilities and equipment are often specialized. The value is low for some retail industries (e.g., restaurants, apparel, and furniture stores) because they are the primary users of operating leases (as we discussed already), so a large part of their PPE consists of store decorations (e.g., leasehold improvements to customize commercial space), which are rather specific. For services (e.g., personal and business services), a substantial fraction of their PPE is equipment, which can have high specificity (equipment represents 75% of PPE for the average Compustat firm in services). Some service industries (e.g., amusement parks) also have specialized real estate. In Section III, we show that physical attributes of PPE (mobility, durability, and customization) can account for the average level of PPE liquidation recovery rates and close to 40% of the variation across industries.[10]

For inventory, the average industry-level liquidation recovery rate is 45%. The value is high for retailers such as auto dealers (88%) and apparel stores (74%), given the generic nature of their inventory. It is low for restaurants (15%), since their inventory primarily consists of perishable fresh food. Finally, Tables II and III also present industry-level liquidation recovery rates for receivables and book intangibles. Receivables have close to full recovery for utilities. In other industries, the values can be lower due to receivables from foreign counterparties and dominant large customers, which are difficult to enforce; some receivables may also be offset by payables to the same entities. We discuss book intangibles in detail in Section IV.B. They represent goodwill and other

9. In an example year (e.g., 2016), among three-digit SIC codes that have any public companies, nearly 80% have fewer than 20 firms. Thus the scope of public companies puts natural limits on the number of observations for which we have liquidation recovery rates.

10. We also verify that the industry-level liquidation recovery rates in our data are not significantly correlated with other industry attributes, such as skill intensity (e.g., the share of workers with a college degree from Current Population Survey data), tangibility (PPE/assets), average Q, and β.

TABLE II

LIQUIDATION RECOVERY RATE BY INDUSTRY AND ASSET TYPE

SIC2	PPE	Inventory	Receivable	Intangible	Nongoodwill intan.
10 Metal mining	0.31	0.44	0.56	0.18	0.18
12 Coal mining	0.23	0.58	0.75	0.24	0.24
13 Oil/gas extraction	0.49	0.42	0.76	0.15	0.18
14 Quarrying—nonmetals	0.53	0.56	0.78	0.00	0.00
15 Building construction	0.28	0.32	0.65	0.00	0.00
17 Construction contractors	0.37	0.20	0.29	–	–
20 Food products	0.37	0.42	0.74	1.40	1.40
22 Textile products	0.43	0.52	0.74	0.25	1.66
23 Apparel products	0.25	0.71	0.70	1.09	1.09
24 Wood products	0.39	0.60	0.53	0.02	0.02
25 Furniture and fixtures	0.27	0.32	0.67	0.13	0.27
26 Paper products	0.31	0.52	0.63	0.06	0.12
27 Printing and publishing	0.31	0.32	0.61	0.14	0.22
28 Chemical products	0.24	0.49	0.64	0.46	0.48
30 Rubber and plastics products	0.43	0.51	0.66	0.11	0.13
32 Stone, clay, glass, and concrete	0.44	0.45	0.72	0.23	0.23
33 Primary metal	0.43	0.64	0.76	0.25	0.25
34 Fabricated metal	0.39	0.46	0.70	0.24	0.27
35 Machinery	0.36	0.36	0.47	0.00	0.00
36 Electronic equipment	0.35	0.32	0.62	0.38	0.45
37 Transportation equipment	0.38	0.60	0.62	0.21	0.21
38 Analytical instruments	0.38	0.37	0.79	0.32	0.32
39 Misc. manufacturing	0.27	0.66	0.69	0.20	0.31
41 Local transit	0.54	0.32	0.72	0.00	0.00
42 Motor freight	0.54	0.34	0.65	0.02	0.05
44 Water transportation	0.49	0.43	0.52	–	–
45 Transportation by air	0.51	0.47	0.39	1.36	1.52
47 Transportation services	0.62	0.36	0.20	0.00	0.00
48 Communications	0.24	0.29	0.57	0.20	0.31
49 Electric and gas	0.50	0.35	0.83	0.44	0.49
50 Wholesale durables	0.33	0.55	0.72	0.06	0.07
51 Wholesale nondurables	0.54	0.55	0.58	0.31	0.48
52 Building materials dealers	0.57	0.29	0.21	0.00	0.00
53 General merchandise stores	0.31	0.54	0.33	–	–
54 Grocery stores	0.36	0.72	0.52	0.13	0.23
55 Automotive dealers	0.04	0.88	0.55	0.01	0.01
56 Apparel stores	0.08	0.74	0.74	0.27	0.30
57 Furniture stores	0.16	0.82	1.00	–	–
58 Restaurants	0.19	0.15	0.57	0.22	0.42
59 Misc. retail	0.28	0.55	0.58	0.60	0.60
70 Lodging	0.50	0.49	0.68	0.37	0.42
72 Personal services	0.23	0.15	0.54	0.00	0.01
73 Business services	0.31	0.44	0.63	0.06	0.10
78 Motion pictures	0.31	0.37	0.48	0.01	0.01
79 Amusement and recreation	0.21	0.31	0.62	0.43	0.44
80 Health services	0.23	0.30	0.44	0.04	0.13
82 Educational services	0.15	0.15	0.37	0.08	0.17
87 Professional services	0.31	0.45	–	–	–

Notes. This table presents the average liquidation recovery rate (liquidation value/net book value) for each asset category in each two-digit SIC code.

TABLE III
SUMMARY STATISTICS

	mean	sd	p25	p50	p75
Panel A: Industry-level liquidation recovery rates					
PPE	35.00	13.11	26.09	34.14	43.91
Inventory	45.40	16.73	32.26	44.49	55.16
Receivable	60.70	15.96	53.32	62.55	72.36
Book intangible	24.83	32.58	2.14	17.58	31.46
Nongoodwill book intangible	32.03	39.63	4.50	22.94	42.44
Panel B: Firm-level total liquidation value					
Chapter 11 liquidation analysis sample					
Total liquidation value/book assets	0.45	0.25	0.27	0.42	0.60
Total liquidation value/going-concern value	0.56	0.33	0.32	0.51	0.74
Compustat firms (2000–2018)					
Total liquidation value/book assets	0.47	0.20	0.33	0.45	0.57
Total liquidation value/going-concern value	0.42	0.37	0.20	0.33	0.53

Notes. This table presents summary statistics for industry-level liquidation recovery rates in Panel A and firm-level total liquidation value of all assets (including cash) in Panel B. The going-concern value for the Chapter 11 liquidation analysis sample uses the postemergence market value of the firm (market value of equity plus book value of debt) if available and estimated going-concern value in the Chapter 11 plan otherwise (e.g., if the firm is private after emergence). The going-concern value for Compustat firms is the market value of equity plus the book value of debt. The mean, standard deviation, and quartiles are presented.

intangibles purchased from outside; many nongoodwill book intangibles can be transferred on a standalone basis (e.g., licenses, data, patents) to generate positive liquidation values. The liquidation recovery rates of book intangibles are high for airlines, some manufacturing industries, and recreation because of transferable licenses and usage rights (e.g., route rights and gate rights, licenses, copyrights), patents, and customer data.

Overall, we find a relatively high degree of asset specificity on average, as well as substantial variations across industries. As mentioned earlier, since our data includes high-specificity assets that are not captured in the secondary market trading of generic assets, the liquidation values could be lower than intuitions based on prototypical assets with large-scale secondary markets.[11] In the next section, we perform extensive checks to ensure that the data do not contain systematic reporting biases; we also address measurement noise.

11. For example, the PPE liquidation recovery rate for air transportation can be lower than that for commercial airplanes alone because airlines' PPE also includes spare parts, ground and training equipment, maintenance facilities, and so on; some airlines also operate more specialized aircraft, such as helicopters.

II.C. Data Informativeness and Generalizability

We perform a number of checks to examine the reliability of the liquidation recovery rate data. We start with concerns about biases and then discuss measurement noise.

For biases, one possible concern is that firms in Chapter 11 may have incentives to understate liquidation values to justify restructuring. However, in our data the median firm's value as an operating business is twice as much as the total liquidation value, so the manipulation incentive may not be very strong. Another concern is that firms in Chapter 11 differ from the typical nonfinancial firm, because Chapter 11 may occur when the firm, its industry, or the economy experiences unfavorable conditions. In terms of economic conditions, about 13% of our data come from recessions dated by the National Bureau of Economic Research (NBER) and 40% from industry recessions (i.e., industry revenue growth in the bottom quartile), so the data do not overwhelmingly represent severe downturns. We address industry conditions as well as firm-specific conditions in more detail below and in Section III.B. A final concern is that if the net book value is overestimated due to firms using depreciation rates that are too small, the liquidation recovery rate can be biased downward. In Online Appendix 7.2, we check that the depreciation rates firms use are similar to those in BEA data.[12]

Through the checks below and analyses of the determinants of liquidation recovery rates in Section III, we verify that our data are consistent with market-based outcomes, including auction results, when such data are available. We also verify that although detailed reporting is mainly available for Chapter 11 firms, our data are consistent with additional information collected from nonfinancial firms more generally. Furthermore, Section IV demonstrates that the data perform well for explaining the outcomes of firms in general.

First, we check with results from auction data. Ramey and Shapiro (2001) analyze equipment liquidations of aerospace manufacturing plants using confidential auction information. They estimate that the equipment liquidation recovery rate is around 28%. In our data, based on the same three-digit SIC (SIC 372),

12. Moreover, firms generally apply linear depreciation, while the BEA uses geometric depreciation. Given the depreciation rate is similar, this implies that the net book value using firms' depreciation methods tend to be smaller, which if anything would bias the liquidation recovery rate upward.

the liquidation recovery rate on machinery and equipment is 32%, which is similar. In addition, we obtain information on auctions of construction equipment from EquipmentWatch (Murfin and Pratt 2019) as well as the equipment vintage and original price. We then compute the replacement cost (book value net of depreciation) using depreciation rate estimation following Ramey and Shapiro (2001). We find that the average liquidation recovery rate is 55% in these auction data, which is similar to the value for construction equipment implied by our data (around 60%).[13]

Second, we compare total estimated liquidation values in Chapter 11 liquidation analyses with liquidation proceeds in Chapter 7. Chapter 7 cases only report total liquidation proceeds, not liquidation recovery rates for each category of asset. As a result, we cannot use these data for our main analyses, where we need to measure the specificity of a given type of asset (e.g., fixed assets). A further complication is that in Chapter 7 the trustee may abandon assets that have little value, or return assets that have negative equity (i.e., assets with liquidation values less than the amount of liabilities against them) to lenders to foreclose. The value of these assets is not included in the reported total Chapter 7 liquidation receipts (Bris, Welch, and Zhu 2006). In the "basic" scenario, we only use the total Chapter 7 liquidation receipts from the trustee report, which may underestimate the total liquidation value. In the "medium" scenario, we add 50% of the value of debt against separable assets (or all secured debt). In the "high" scenario, we add 100% of the value of such debt. Adding the value of debt against separable assets assumes that the value of abandoned assets covers 50% or 100% of debt against separable assets; the latter case should overestimate the liquidation value of abandoned assets. For firms in the same industry, Online Appendix Table 2 shows that estimated total liquidation values (normalized by total assets at filing) in Chapter 11 liquidation analyses are similar to total proceeds in Chapter 7 liquidations.

Third, the average liquidation recovery rates in our data align closely with benchmarks used by creditors when they lend against

13. In particular, our liquidation recovery rate data is at the industry level and construction equipment (e.g., aerial lift, graders) can be used in multiple industries. Accordingly, to isolate the liquidation recovery rate of construction equipment implied by our data, we use Table IV, Panel A and apply the transportation cost, design intensity, and depreciation rate of construction equipment available from BEA data. The implied liquidation recovery rate is around 60% based on column (1).

particular assets such as PPE and working capital, which reflect their assessments of the liquidation values of nonfinancial firms in general (Udell 2004). For instance, lenders on average lend 20% to 30% against the book value of PPE according to a large bank, which is similar to the average PPE liquidation recovery rate of 35% in our data. Benchmarks that lenders use for inventory and receivable are also similar to the average liquidation recovery rates of these assets in our data.[14]

Fourth, we use imputed recovery rates from PPE sales among Compustat firms to cross-check the average PPE liquidation recovery rate in our data. Specifically, firms' financial statements report proceeds from sales of PPE (Compustat variable SPPE). However, the net book value of PPE sold is not reported, so we need to impute it (using the formula net PPE in current year = net PPE in previous year + capital expenditures − depreciation − PPE sold). This imputation is noisy because firms' PPE stock can change for other reasons; we exclude firm-years with mergers or division spinoffs as these events can have a major impact on the PPE stock. If we directly divide PPE sale proceeds by the net book value sold, the median ratio is 0.47 (the mean is affected by extreme outliers due to imperfect imputation of the denominator). Alternatively, we estimate the average sale recovery rate by regressing the PPE sale proceeds on the net book value sold (both variables are normalized by lagged net PPE) and find a coefficient of 0.31. Overall, these estimates implied by PPE sales among Compustat firms are in line with the average liquidation recovery rates in our data. Because the imputed PPE sale recovery rates are very noisy, we do not use them for our main analyses. Moreover, these sales only capture a small subset of PPE (PPE sale proceeds are less than 1% of net PPE for the majority of firm-years with sales), so the assets selected to be sold may not be representative.

14. Creditors on average lend 50% to 60% against the book value of eligible inventory (see also OCC Comptroller's Handbook on Asset-Based Lending), where about 80% of inventory is eligible (e.g., work-in-progress inventory often ineligible), which implies a total inventory liquidation recovery rate of 40%–48%. In our data, the average industry-level inventory liquidation recovery is 44%. Creditors on average lend 80% against the book value of eligible receivables (see also the OCC handbook), where about 80% of receivables are eligible (e.g., government receivable and foreign receivable are typically not eligible), which implies a total receivable liquidation recovery rate of 64%. In our data, the average industry-level receivable liquidation recovery rate is 61%.

Finally, in Section III, we document that both the level and the cross-industry variations of liquidation recovery rates are well explained by the physical attributes of assets used in different industries, measured among all firms in each industry. Industry conditions can affect liquidation recovery rates, but they do not easily erase differences across industries or lead to drastically different overall liquidation recovery rates. Franks et al. (2022) suggest that airplanes sold by airlines in bankruptcy have lower quality, and the quality difference contributes to 9% lower prices for aircraft sold by airlines in Chapter 11. Given the magnitude of this effect, it also does not change the overall picture of low liquidation recovery rates (if liquidation values are 9% higher, the overall picture remains similar).

For measurement noise, the key question is whether our industry-level liquidation recovery rate is reliable (we need the industry-level measures to apply the data more broadly). One check is that we can examine the liquidation recovery rate in a given case i as a function of the average liquidation recovery rate of other cases in the same two-digit industry. We run the following regression:

$$\lambda_{ijk} = \alpha + \beta \bar{\lambda}_{(-i)jk} + \epsilon_{ijk}, \tag{1}$$

where λ_{ijk} is the liquidation recovery rate of asset type k in case i of industry j and $\bar{\lambda}_{(-i)jk}$ is the average liquidation recovery rate of asset type k of all other cases in industry j (excluding case i). For the liquidation recovery rate of fixed assets, if we run the regression in equation (1) in industries with more than 3 (5) cases, then we obtain a slope coefficient β of 0.63 (0.70) with a standard error of 0.11 (0.11). This "leave-one-out" exercise suggests that the industry-level liquidation recovery rate is reasonably informative for an individual firm, although measurement noise and firm-specific variation could exist.

Relatedly, another check is that we can randomly split the cases in each industry into two halves, $G1$ and $G2$, and calculate the average liquidation recovery rate for each half ($\bar{\lambda}^{G1}_{jk}$ and $\bar{\lambda}^{G2}_{jk}$). For instance, if we regress $\bar{\lambda}^{G1}_{jk}$ on $\bar{\lambda}^{G2}_{jk}$, limiting to industries with more than 3 (5) cases, then we obtain a slope coefficient of 0.66 (0.86) with a standard error of 0.19 (0.18) and an F-stat of 12 (24). Accordingly, in applications of the liquidation recovery rate data, we can instrument the average liquidation recovery rate from $G1$ with that from $G2$ to further reduce measurement noise (as long as the noise in $\bar{\lambda}^{G1}_{jk}$ and $\bar{\lambda}^{G2}_{jk}$ are independent). We can also use the liquidation recovery rate predicted by assets' physical attributes obtained in Section III.A to reduce noise.

Overall, the results suggest that the average liquidation recovery rate in each industry can be a good (albeit noisy) measure of the relevant liquidation recovery rate that applies to firms in the industry. Even though noisy measurement may weaken the empirical results, we show that the data are informative for explaining firms' investment and financial decisions in Section IV and in Kermani and Ma (2022b).

II.D. Firm-Level Liquidation Values

Using the industry-level liquidation recovery rates for each category of assets on firms' balance sheets, we also calculate the estimated firm-level liquidation value for Compustat firms, which we use in Section IV. In particular, for Compustat firms we construct:

$$Liq_{i,t} = \sum_{j} \lambda_{i,j} K_{i,j,t}, \tag{2}$$

where $Liq_{i,t}$ is the total liquidation value of firm i at time t, j denotes the asset type (e.g., PPE, inventory), $\lambda_{i,j}$ is the industry-average liquidation recovery rate for this type of asset (based on the firm's industry), and $K_{i,j,t}$ is the book value of asset j for firm i at time t. These firm-level liquidation value estimates assume that asset attributes in an industry are broadly similar. While there can be variations across firms in an industry due to location, equipment vintage, or other factors (as is well acknowledged by appraisal specialists), we need an industry-level aggregation of liquidation recovery rates to make the data more widely applicable. Our checks verify the informativeness of the industry-level liquidation recovery rates. Table III, Panel B shows summary statistics of firm-level liquidation values. We have data for firms in the Chapter 11 liquidation analysis sample. We also estimate these values for Compustat firms using equation (2). For firms in both samples, the total liquidation value including all types of assets (PPE, inventory, receivable, cash, etc.) is on average around 45% of total book assets. The interquartile range is about 30%–60%.

As explained at the beginning of this section, for each type of asset, we normalize its liquidation value by its book value.

Nonetheless, for the firm as a whole, we can also compare its total liquidation value with its going-concern value (i.e., value as an operating business). This comparison sheds light on the "intrinsic" value of standalone assets if the firm is "dead," relative to the present value of cash flows from the firm's operations if it is "alive." For firms in the Chapter 11 sample, we directly observe the assessment of their total liquidation values and going-concern values (we use postemergence firm market values for those that emerged as public firms and estimated going-concern values in the Chapter 11 confirmation plans otherwise). The median ratio is 51% (interquartile range 32%–74%). For Compustat firms, we compare their estimated total liquidation values $Liq_{i,t}$ including all major types of assets with their going-concern values (debt plus market value of equity). The median ratio is 33% (interquartile range 20%–53%). The data suggest that in most cases, if a living firm were to be dismantled into only its standalone separable assets, a substantial amount of value could dissipate. These results also highlight the importance of legal institutions that preserve viable firms as operating businesses (e.g., through effective restructuring-based bankruptcy systems) rather than liquidate them (Djankov et al. 2008; Kermani and Ma 2022b).

Overall, liquidation values are limited for many firms. This feature is traditionally associated with industries such as technology, but it is indeed a more general phenomenon.

III. Determinants of Asset Specificity

In this section, we investigate the key determinants of asset specificity. We analyze what explains variations in liquidation recovery rates across industries and over time. In Section III.A, we demonstrate the importance of physical attributes of the assets used in different industries. In Section III.B, we examine the impact of economic conditions. We focus on fixed assets below and analyze inventory and other assets in Online Appendices 5 and 6.

III.A. Physical Attributes

We analyze three physical attributes that can affect the specificity of PPE. The first attribute is mobility: some assets are mobile (e.g., aircraft, ships, vehicles), which helps them reach alternative users more easily, whereas other assets are costly to transport or location-specific (e.g., assembly lines, roller coasters). The second attribute is the degree of customization: some assets are standardized, in which case other firms can use them more easily, while other assets are customized for a particular user. The third attribute is durability: reallocation takes time, and assets that depreciate faster can be less valuable by the time they reach alternative users (fresh food is an extreme example). As we illustrate in the model in Online Appendix 3, all of them can affect the asset's liquidation value. The model also examines how search frictions can affect the impact of physical attributes.

We focus on these three attributes also because they can be measured consistently for different types of assets, and we explain the measurement below.

1. *Measurement of Physical Attributes.* To measure the physical attributes of PPE in each industry, a helpful starting point is the BEA's fixed asset tables, which record the stock of 38 types of equipment and 32 types of structures across 58 BEA industries. We list the 70 types of fixed assets in Online Appendix Table 14. For BEA industry i (which is roughly at the level of two-digit SIC codes) and asset type j, we denote the stock as K_{ij}. We analyze the physical attributes of each type of fixed asset (j) with the help of the BEA's input-output tables and then take the weighted average across asset types to assess the overall characteristics of fixed assets in an industry (i), where the weights come from the fixed-asset composition (the share of K_{ij} in $K_i = \sum_j K_{ij}$).[15]

Mobility: We measure the mobility m_j for each type of equipment using the ratio of its transportation costs (from producers to users) to its production costs, which we obtain from the BEA's input-output tables. Transportation cost data are available for equipment, but they are not well defined for structures. Therefore, we construct the transportation cost measure for the 38 types of equipment in the BEA fixed asset tables and control for the equipment share in total fixed assets (around 50% in the average industry). To verify the informativeness of the transportation cost

15. We exclude the category "nuclear fuel," which does not appear to be a type of fixed asset. The stock of fixed assets in each industry in the BEA data is based on ownership, that is, the asset stock of each industry includes owned assets and assets under capital lease (which implies ultimate ownership) and does not include assets under operating leases (where ownership belongs to the lessor not the lessee). This is the same convention as our data on liquidation recovery rates, which includes all assets that firms own and does not include assets under operating lease, as discussed in Section II.A.

data, we collect data on the weight to value ratio for each type of equipment from the Census Commodity Flow Survey (CFS). We find that our transportation cost measure is significantly higher for heavier assets, shown in Online Appendix Table 15.[16]

We calculate the industry-level PPE mobility M_i by taking the weighted average across the 38 types of equipment, where the weight is the share of the asset in the industry's total equipment stock based on the BEA fixed asset tables: $M_i = \sum_j m_j \times \frac{K_{ij}}{K_i}$. Accordingly, the industry-level mobility measure is the ratio of total transportation costs of all equipment to the total production costs of all equipment. We match BEA industries with two-digit SICs (the industry codes in our liquidation value data).

Customization: We construct a proxy for the degree of customization c_j for each type of PPE using the share of design costs in its total production costs (i.e., we look at what it takes to produce each type of PPE). The idea is that customized assets tend to require more design. For each of the 70 fixed assets, we calculate this share using the BEA's input-output tables.[17] Specifically, we find the sector that produces each type of PPE in the input-output tables similar to Vom Lehn and Winberry (2022), and record the producer sector's spending on design as a share of the total production costs. To check the reliability of the customization measure, we build on the idea that customized assets are less likely to be sold through wholesalers and retailers. For each type of equipment, we can use the CFS data to calculate the fraction of its total domestic shipment where the shipper is a wholesaler or a retailer (unfortunately we cannot apply this check to structures). We find that this measure is negatively correlated with our customization measure, shown in Online Appendix Table 15.

We calculate the industry-level PPE customization C_i by taking the weighted average across the 70 types of assets:

16. Assets with higher transportation costs also have lower average miles transported according to the CFS data, which is suggestive that the set of alternative users they can reach is likely to be more limited.

17. We calculate design and related costs using the following categories: design, information services, data-processing services, custom computer-programming services, research, advertising, management consulting, business support services, and miscellaneous professional and technical services. These are categories possibly related to customization. If we use a narrower definition (e.g., excluding advertising, management consulting, support services), the measure is over 90% correlated with the broader measure (even though the level is different) and the main results are similar.

$C_i = \sum_j c_j \times \frac{K_{ij}}{K_i}$. Correspondingly, the industry-level customization measure is the share of design costs in total production costs of all PPE in each industry. We match BEA industries with two-digit SIC codes.

Durability: We measure the durability of assets using depreciation rates. The simplest approach is to calculate the average depreciation rate of PPE (depreciation divided by lagged PPE) in each two-digit SIC industry using Compustat data, which avoids translating BEA industries to SIC codes.

Other Attributes: Several previous studies use the overall market size of an asset to measure its market thickness and correspondingly its redeployability. For instance, Gavazza (2011) and Benmelech and Bergman (2009) analyze the airline industry and measure the redeployability of a given type of aircraft using the number of planes or operators. Benmelech (2009) studies railroads in the nineteenth century and measures redeployability using the size of railroads with a certain gauge. Conceptually, the physical attributes discussed above may affect market thickness (e.g., if an asset is highly customized, the number of possible users would be small and the market is likely to be thin). Empirically, a systematic measure of market thickness across different types of assets can be challenging to construct. In particular, a given type of aircraft or railroad equipment is reasonably well defined. For a broader set of assets (e.g., the 70 types of assets in the BEA fixed-asset tables), the market size is harder to measure, and the result can depend on the granularity of each asset category. For instance, the largest asset category in the BEA fixed-asset tables is manufacturing structures; if the BEA alternatively breaks down manufacturing structures by type (e.g., food, chemical, metal), then the size for each type of manufacturing structure would be smaller. Relatedly, Kim and Kung (2017) construct a proxy for asset redeployability using the number of industries that purchase a certain type of asset in the BEA capital flow table. The granularity of the BEA's asset categories can also affect this approach (e.g., if the BEA data have separate categories for different types of manufacturing plants instead of a general category for all industrial plants then the number of purchasing industries will shrink).[18]

18. The Kim and Kung (2017) measure does not seem to explain the PPE liquidation recovery rates in our data. A redeployability proxy that focuses on the number of industries purchasing a given type of asset may also omit other relevant factors: for instance, some of the most mobile and durable assets are used

Finally, Rauch (1999) provides a classification of commodities in international trade based on whether they are traded on organized exchanges, which has been used as a proxy for specificity (Nunn 2007). Because the commodities in Rauch (1999) map more closely into inventory, we provide further discussions when we investigate the determinants of inventory liquidation recovery rates in Online Appendix 5. In particular, the trading arrangement of commodities can be influenced by commodities' physical attributes, and we find that commodities with more customization (higher design cost share in total production costs) are significantly less likely to be traded on organized exchanges.[19]

In sum, we focus on three measures of physical attributes (mobility, customization, and durability) that can be consistently constructed across industries for all types of assets. Although these attributes may not be exhaustive, we document that they have substantial explanatory power for the liquidation values of fixed assets. We use the 1997 BEA fixed-asset tables and input-output tables to construct the physical attribute measures. Since the BEA only produces input-output accounts every five years, 1997 provides comprehensive information and predates our liquidation recovery rate data. Online Appendix Table 16 shows the industry-level summary statistics for two-digit SIC industries.

2. *Explanatory Power of Physical Attributes.* In Table IV, Panel A, we study the relationship between the physical attributes and the liquidation recovery rates of PPE across industries. Columns (1) and (2) use two-digit SIC industries; columns (3) and (4) use BEA industries. We find that physical attributes have

in only a few industries (e.g., ships and aircraft), whereas some assets used in many industries can be costly to move and much less durable (e.g., computers). Finally, the Kim and Kung (2017) measure happens to be significantly correlated with the quantity of fixed assets (PPE as a share of book assets or "tangibility"). In particular, higher firm-level redeployability in the Kim and Kung (2017) data happens to be associated with less fixed assets. This relationship seems to affect some of the results in their analyses such as the effect of asset redeployability on the sensitivity of investment to uncertainty.

19. The literature has also discussed the concept of relationship specificity, which is related to asset specificity, but they are not always the same. First, assets can be specific to a certain user not only due to trading relationships but also other reasons such as transportation costs, special design, and perishability (e.g., aquariums, eyeglasses, fresh food). Second, the asset specificity we measure focuses on nonhuman assets, but relationship specificity can also apply to human capital (Williamson 1996).

TABLE IV
DETERMINANTS OF PPE LIQUIDATION RECOVERY RATES

	Industry-level PPE liquidation recovery rate			
	Two-digit SICs		BEA industries	
	(1)	(2)	(3)	(4)
Panel A: Physical attributes and industry-average liquidation recovery rates				
Transportation cost	– 4.75**	– 4.71**	– 3.60**	– 3.50**
	(1.95)	(1.99)	(1.46)	(1.35)
Design cost share	– 45.48***	– 45.45***	– 46.64***	– 46.31***
	(12.56)	(12.84)	(16.28)	(16.21)
Depreciation rate	– 0.47***	– 0.47***	– 0.62**	– 0.60**
	(0.11)	(0.11)	(0.23)	(0.24)
Equipment share (demeaned)	0.98***	0.98***	0.97***	0.97***
	(0.21)	(0.21)	(0.32)	(0.32)
Industry size (sales share)		0.14		
		(0.61)		
Industry size (value-added share)				– 0.40
				(1.08)
Constant	1.29***	1.28***	1.33***	1.32***
	(0.24)	(0.25)	(0.30)	(0.30)
Observations	48	48	44	44
R^2	0.38	0.38	0.32	0.32

	Case-level PPE liquidation recovery rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Impact of economic conditions						
Industry sales growth	0.153**	0.160*				
	(0.070)	(0.080)				
Industry value-added growth			0.140**	0.162**		
			(0.052)	(0.065)		
Industry leverage					−0.204***	−0.214**
					(0.064)	(0.088)
Sales/assets		0.006		0.007		0.006
		(0.025)		(0.024)		(0.024)
Liabilities/assets		0.041		0.042*		0.043*
		(0.024)		(0.023)		(0.025)
Fixed effect	Industry					
Observations	400	372	400	372	400	372
R^2	0.012	0.040	0.007	0.035	0.012	0.040

TABLE IV
CONTINUED

Notes. This table examines the determinants of PPE liquidation recovery rates. Panel A presents industry-level regressions that study the relationship between the physical attributes of assets in each industry and the industry-average PPE liquidation recovery rate. Transportation cost (relative to total production cost of PPE) measures mobility. Design cost share (in total production cost of PPE) measures customization. Depreciation rate measures durability. Equipment share is the fraction of equipment in each industry's total fixed assets from BEA fixed-asset tables. Sales share of an industry in Compustat and value-added share of an industry in BEA data capture industry size. All attributes are measured using BEA and Compustat data in 1997. Columns (1) and (2) use two-digit SIC codes; columns (3) and (4) use BEA industries. Panel B presents case-level regressions that study the relationship between macro and industry conditions and the firm-level liquidation recovery rate within each industry. Industry sales growth is the average sales growth in Compustat data over the past four quarters prior to the liquidation analysis, industry value-added growth is the value-added growth of the industry in national accounts over the past year, and industry leverage is average debt/assets in Compustat data in the quarter prior to the liquidation analysis. Sales/assets and liabilities/assets capture financial ratios of each company at the time of the Chapter 11 filing. Industry fixed effects (two-digit SICs) are included. R^2 does not include industry fixed effects. Robust standard errors are presented in parentheses in Panel A. Standard errors clustered by time and industry are presented in parentheses in Panel B. *** $p = 1\%$, ** $p = 5\%$, * $p = 10\%$.

substantial explanatory power for PPE liquidation recovery rates. First, the regression coefficients show that industries where PPE has high transportation costs, high degrees of customization, or high depreciation rates have low PPE liquidation values. A higher equipment share is also associated with higher PPE liquidation values, consistent with the observation of Ramey and Shapiro (2001). Second, the constant is around one (at the average level of equipment share of around 50%), indicating that when physical frictions for reallocation are absent—namely, if PPE is costless to transport, not customized, and fully durable—then the liquidation recovery rate would be slightly over 100%. In other words, the physical attributes perform well in explaining why the level of liquidation recovery rate is less than one in most industries. Third, the R^2 of 30%–40% suggests that the physical attribute measures account for a meaningful amount of the variations in PPE liquidation recovery rates. Given that these measures are inevitably imperfect, the true explanatory power of physical attributes could be higher. In columns (2) and (4), we include measures of industry size (an industry's sales share in Compustat and value-added share in BEA data). We do not find significant results for this general measure of industry size.

We take a closer look at the contribution of each key physical attribute. In terms of the economic magnitude, based on column (1), a one standard deviation change in mobility (transportation cost), customization (design cost), and durability (depreciation rate) is associated with changes in PPE liquidation recovery rate of 0.36, 1.15, and 0.35 standard deviations, respectively. Another assessment is to calculate how much the PPE liquidation recovery rate is predicted to change if we set each variable to zero. If we set the transportation cost measure to zero, then PPE liquidation recovery rate would increase by 12 percentage points on average. The values for design intensity and depreciation rate are 58 and 11 percentage points, respectively.

One possible concern related to the depreciation rate is the following. The liquidation process takes time (six months to a year, as discussed in Section II) and the net book value (the denominator in the liquidation recovery rate) is measured at the beginning of the liquidation process. Thus this book value may be higher than the net book value by the time the asset is sold, which would reduce the liquidation recovery rate, especially for assets that depreciate quickly. In Online Appendix Table 4, we depreciate the book value by another six months and show that the results are similar. Note that if selling and transferring the asset takes time (so the asset is not used for production during this process), then the relevant measure is closer to our baseline liquidation recovery rate.

In summary, we find that the degree of asset specificity is closely linked to assets' physical attributes, given by the nature of production activities in each industry. The physical attributes of fixed assets measured using independent data sources have a strong explanatory power for PPE liquidation recovery rates in our data. Given the low liquidation values of production assets and the role of physical attributes that contribute to reallocation frictions, our results corroborate that production assets are far from generic; accordingly, search and matching frictions can be important for modeling the secondary market of production assets.

III.B. Economic Conditions

Next we examine how economic conditions affect PPE liquidation values. A number of studies suggest that time-varying economic conditions influence the capacity of alternative users (Shleifer and Vishny 1992; Kiyotaki and Moore 1997; Lanteri 2018). In Table IV, Panel B, we use three variables to capture industry conditions: (i) industry-average sales growth in Compustat over the past four quarters prior to the liquidation analysis, (ii) industry value-added growth in national accounts over the past year, and (iii) industry-average book leverage (debt/assets) in Compustat in the quarter prior to the liquidation analysis. We analyze the PPE liquidation recovery rate of each firm and control for industry fixed effects to study how the liquidation recovery rate in an industry changes over time with economic conditions.

We find that PPE liquidation recovery rates are higher when industry sales growth and value-added growth are higher. In terms of magnitude, when industry growth increases by 10 percentage points, liquidation recovery rates on average increase by around 1.5 percentage points. The standard deviation of industry growth is about 15 percentage points, so a two standard deviation change in industry growth would on average shift PPE liquidation recovery rates by less than 5 percentage points. In addition, we find that PPE liquidation recovery rates are lower when industry leverage is higher, which is also consistent with Shleifer and Vishny (1992). In terms of magnitude, when industry leverage increases by 10 percentage points, liquidation recovery rates on average decrease by 2 percentage points. The standard deviation of industry leverage is about 18 percentage points, so a two standard deviation change in industry leverage would on average shift PPE liquidation recovery rates by 7 percentage points. Overall, the magnitude is mild; the R^2 generated by the measures of industry conditions is also small. Variation in industry conditions does not seem to dramatically change the general level of liquidation recovery rates; it also does not easily change the differences across industries (e.g., industry conditions need to change by more than two standard deviations to shift the PPE liquidation recovery rate by more than one quartile). Finally, we do not find a significant relationship between liquidation recovery rates in our data and economy-wide GDP growth; industry-specific conditions appear more relevant.

In the even columns, we also include firm-specific conditions, which cover sales/assets and liabilities/assets at the time for each Chapter 11 filing (these are the main financial variables with good coverage, though still missing for a few firms). We do not find a significant relationship between the liquidation recovery rate and these firm characteristics. The conditions of a given firm may not have a strong link with the liquidation value of its physical assets because the liquidation value represents the value in alternative use (e.g., the real estate of a bookstore making losses may have high liquidation value, whereas the customized equipment of a pharmaceutical company making profits may have little liquidation value).

To further investigate the impact of industry conditions and strengthen the external validity of the results using our liquidation analysis data, we examine over 80,000 auctions of construction equipment between 1994 and 2013 (we analyzed the average auction recovery rate in this data set from Murfin and Pratt 2019 in Section II.C). In Online Appendix Table 5, we perform regressions of the auction recovery rate (i.e., auction value/purchase price net of depreciation) on the same three variables for industry conditions in Table IV, Panel B, measured for the construction industry. The results are consistent with what we observe in Table IV, Panel B, and the magnitude of the coefficients on industry conditions is largely similar.

In summary, our results provide evidence for cyclical variations in liquidation values; nonetheless, these fluctuations do not change the overall picture of high asset specificity.

IV. Implications

Here, we examine the leading implications of asset specificity. In Section IV.A, we study the consequences of investment irreversibility. We show that disinvestment is less common when asset specificity is high. Moreover, we provide direct evidence that uncertainty negatively affects investment when assets are specific, whereas the effect is absent when assets are generic. In Section IV.B, we illuminate the economic impact of intangible capital. We demonstrate that in contrast to conventional wisdom, intangibles have not had a first-order effect on firms' liquidation values. In Section IV.C, we summarize several additional applications. The analyses in this section use all nonfinancial firms in Compustat, combined with our asset specificity data based on industry.[20] Accordingly, in addition to demonstrating the implications of asset specificity, the results also show that our data performs well for explaining the behavior of firms in general.

20. Online Appendix Table 6 present the summary statistics of the Compustat sample. We use the sample period 1985–2018, where data on firms' investment spending is available both annually and quarterly. We winsorize outliers at the 1% level.

IV.A. Investment Irreversibility

Investment irreversibility is a prominent theme in theories of investment (Bernanke 1983; Pindyck 1991; Caballero 1999; Bloom 2009; Bloom et al. 2018). When asset specificity is higher, disinvestment is more costly and irreversibility is stronger. We start by documenting that disinvestment is indeed less common in such cases, which verifies that disinvestment frictions are more severe. We then investigate how asset specificity shapes the impact of uncertainty on investment activities.

1. *Prevalence of Disinvestment.* When assets have high specificity and low liquidation values, firms lose more from directly selling these assets. Accordingly, we should expect a lower prevalence of asset sales on a standalone basis. For firms in Compustat, we can measure the prevalence of disinvestment through fixed asset sales using the variable "Sale of Property, Plant, and Equipment" (SPPE), which records proceeds from PPE sales. In Table V, we study the relationship between PPE liquidation recovery rates and the frequency of PPE sales. In columns (1) and (2), we perform firm-level regressions where the outcome variable is an indicator that equals one if a given firm-year has positive PPE sales (SPPE > 0). The key independent variable is the PPE liquidation recovery rate in the firm's industry, and we control for a number of firm characteristics (e.g. Q, leverage). In columns (3) and (4), we perform industry-level regressions where the outcome variable is the fraction of firm-years in each industry with positive PPE sales (SPPE > 0).[21] One possible concern is that PPE liquidation recovery rates may be low because many firms sell fixed assets for certain reasons. If this happens, it will work against us by generating a negative relationship between the prevalence of PPE sales and PPE liquidation recovery rates. To address such concerns, in columns (2) and (4) we use PPE liquidation recovery rates predicted by physical attributes (according to column (1) of Table IV, Panel A). This analysis using the predicted PPE liquidation recovery rates may also alleviate the influence of measurement noise.

Results in Table V show that when PPE has higher irreversibility (lower liquidation recovery rates), the frequency of PPE

21. We do not use the proceeds of sales (e.g., SPPE normalized by lagged net PPE) because this variable can be mechanically lower when liquidation values are lower.

TABLE V

PPE LIQUIDATION RECOVERY RATES AND THE PREVALENCE OF PPE SALES

	Frequency of PPE sales			
	Firm level		Industry level	
	(1)	(2)	(3)	(4)
PPE liquidation recovery rate	0.486*		0.475**	
	(0.279)		(0.187)	
Predicted PPE liquidation recovery rate		1.015***		1.000***
		(0.370)		(0.271)
Q	– 0.027***	– 0.025***		
	(0.003)	(0.004)		
Debt/assets	0.069*	0.064*		
	(0.038)	(0.037)		
Cash/assets	– 0.345***	– 0.325***		
	(0.045)	(0.035)		
EBITDA/l.assets	0.014	0.015		
	(0.012)	(0.011)		
Log(assets)	0.019**	0.017*		
	(0.009)	(0.009)		
Observations	91,706	91,706	48	48
R^2	0.09	0.10	0.15	0.25

Notes. This table shows regressions that study the relationship between PPE liquidation recovery rates and the prevalence of disinvestment in the form of PPE sales. In columns (1) and (2), we perform firm-level regressions where the outcome variable is an indicator that equals 1 if a given firm-year has positive PPE sales (SPPE > 0). The control variables include Q (market value of assets/book value of assets), book leverage, cash holdings (normalized by book assets), EBITDA (normalized by lagged book assets), and size (log book assets) at the end of the previous year. In columns (3) and (4), we perform industry-level regressions where the outcome variable is the fraction of firm-years in that industry with positive PPE sales. In columns (1) and (3), we use the raw industry-level PPE liquidation recovery rates; in columns (2) and (4), we use the PPE liquidation recovery rates predicted by physical attributes (from column (1) of Table IV, Panel A). The sample is Compustat firms from 1985 to 2018. Standard errors are clustered by industry (two-digit SIC) and year in columns (1) and (2), and robust standard errors are presented in parentheses in columns (3) and (4). *** $p = 1\%$, ** $p = 5\%$, * $p = 10\%$.

sales is substantially lower. In terms of economic magnitude, a 10 percentage point increase in the PPE liquidation recovery rate is associated with a 5–10 percentage point higher annual probability of having PPE sales. Figure I visualizes the relationship at the industry level, which shows that the average frequency of PPE sales per year (y-axis) is lower for industries with lower PPE liquidation recovery rates (the x-axis). Panel A uses the direct measure of the PPE liquidation recovery rate, and Panel B uses the predicted value based on physical attributes (according to column (1) of Table IV, Panel A). Taken together, the data shows that low liquidation recovery rates are associated with impediments for

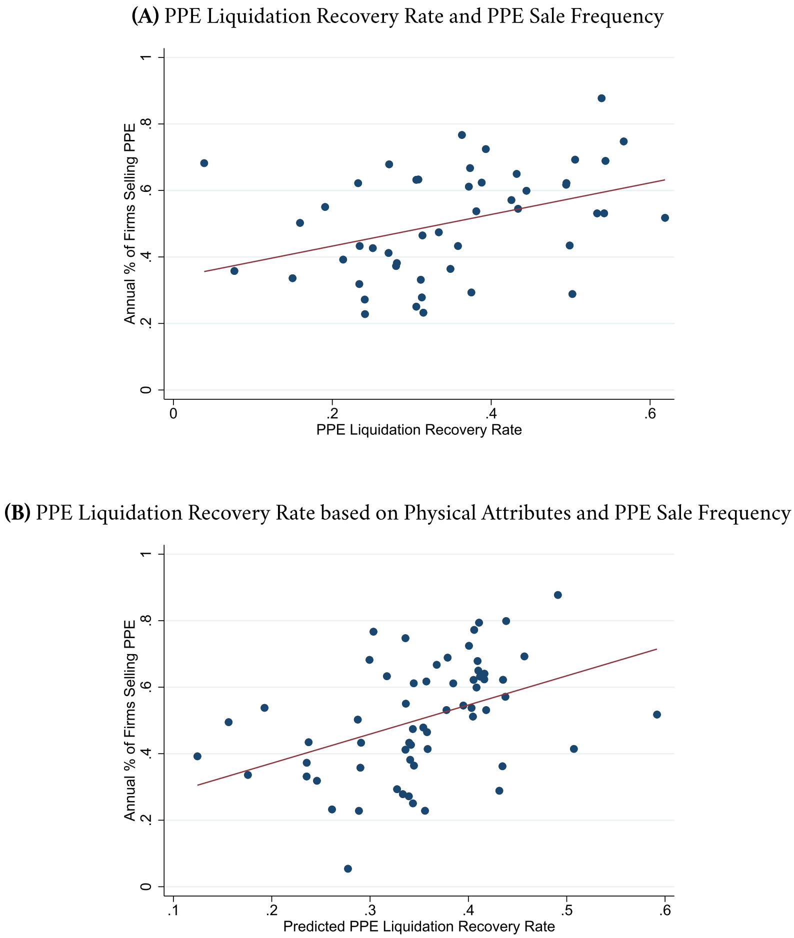


FIGURE I

Asset Specificity and Prevalence of Disinvestment

This figure shows the relationship between the PPE liquidation recovery rate and the prevalence of PPE sales. The y-axis is the industry-average frequency of having nonzero PPE sales (Compustat variable SPPE greater than zero). The x-axis is the industry-average PPE liquidation recovery rate in Panel A and the value predicted by the physical attributes of PPE (using column (1) of Table IV, Panel A) in Panel B. The sample is Compustat firms from 1985 to 2018. Each industry is a two-digit SIC code.

disinvestment, and direct sales of fixed assets are substantially less common in these situations.

2. *Investment Sensitivity to Uncertainty.* A further implication of investment irreversibility is that uncertainty negatively affects investment activities (see Bloom 2014 for a summary). We investigate this prediction in detail in Table VI. We use the following firm-level annual regression to study how the investment response to uncertainty varies with the degree of asset specificity:

$$Y_{i,t+1} = \alpha_i + \eta_{j,t} + \beta\sigma_{i,t} + \phi\lambda_i \times \sigma_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}. \tag{3}$$

For the uncertainty measure $\sigma_{i,t}$, we use both the daily volatility of a firm's stock returns over the previous year and the volatility of abnormal returns (based on the Fama-French three factor model) à la Gilchrist, Sim, and Zakrajšek (2014). The liquidation recovery rate is denoted by λ_i, which is matched to Compustat firms by industry. The outcome $Y_{i,t+1}$ is the investment rate in year $t + 1$ to allow for lags in investment implementation (Lamont 2000). This specification also alleviates concerns about a reverse impact of investment behavior on stock return volatility. We control for the first moment as well, namely the level of stock returns over the previous year. Other control variables in $X_{i,t}$ include Q, book leverage, cash holdings, EBITDA, and size (log book assets) at the end of year t, as well as the level of stock returns in year t and its interaction with λ. We include firm fixed effects (α_i) and industry-year fixed effects ($\eta_{j,t}$), and double-cluster standard errors by industry (two-digit SIC) and year.

In Table VI, Panel A, columns (1) to (2) we start with capital expenditures (i.e., investment in PPE) as the outcome variable, normalized by lagged net PPE. In this case, we use the PPE liquidation recovery rate for λ. We find that higher uncertainty is associated with significant decreases in capital expenditures when the PPE liquidation recovery rate is low, but not when the PPE liquidation recovery rate is high. Indeed, when the PPE liquidation recovery rate is zero, the coefficient on volatility (β) is significantly negative; when the PPE liquidation recovery rate is one, the coefficient on volatility ($\beta + \phi$) becomes roughly zero. Compared to previous studies using indirect proxies of asset specificity, our direct measure has a natural unit, which helps us evaluate the effect of uncertainty when the liquidation recovery rate is zero

TABLE VI
ASSET SPECIFICITY AND INVESTMENT RESPONSE TO UNCERTAINTY

	CAPX invest rate		Inventory invest rate	
	(1)	(2)	(3)	(4)
Panel A: Baseline results				
Vol	−2.65***		−3.44***	
	(0.40)		(0.43)	
Vol × PPE liquidation recovery rate	2.99**			
	(1.37)			
Vol × Invt liquidation recovery rate			2.63***	
			(0.83)	
Abnormal vol (3-fac)		−1.98***		−2.75***
		(0.32)		(0.45)
Abnormal vol (3-fac) × PPE liquidation recovery rate		2.60**		
		(1.17)		
Abnormal vol (3-fac) × Invt liquidation recovery rate				2.09**
				(0.97)
Controls	Yes			
Fixed effect	Firm, industry-year			
Observations	104,505	104,155	84,617	84,396
R^2	0.08	0.08	0.06	0.06

TABLE VI
CONTINUED

	CAPX invest rate		Inventory invest rate		Employment growth	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Additional results						
Vol	−3.33***		−3.44***		−2.05***	
	(0.53)		(0.61)		(0.60)	
Vol × PPE liquidation recovery rate	3.09**		0.03		1.40	
	(1.31)		(1.56)		(1.03)	
Vol × Invt liquidation recovery rate	1.52		2.62***		0.50	
	(0.90)		(0.81)		(0.63)	
Abnormal vol (3-fac)		−2.46***		−2.61***		−1.79***
		(0.42)		(0.68)		(0.60)
Abnormal vol (3-fac) × PPE liquidation recovery rate		2.67**		−0.39		1.37
		(1.15)		(1.88)		(1.19)
Abnormal vol (3-fac) × Invt liquidation recovery rate		1.07		2.07**		0.52
		(0.75)		(0.95)		(0.66)
Controls	Yes					
Fixed effect	Firm, industry-year					
Observations	104,505	104,155	84,617	84,396	101,716	101,398
R^2	0.08	0.08	0.06	0.06	0.07	0.06

Notes. This table presents firm-level annual regressions on how the investment response to uncertainty varies with asset specificity: $Y_{i,t+1} = \alpha_i + \eta_{j,t} + \beta\sigma_{i,t} + \phi\lambda_i \times \sigma_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$. In Panel A, columns (1) and (2), $Y_{i,t+1}$ is annual capital expenditures (normalized by lagged net PPE), and λ_i is the PPE liquidation recovery rate based on firm i's industry. In columns (3) and (4), $Y_{i,t+1}$ is annual inventory growth, and λ_i is the inventory liquidation recovery rate based on firm i's industry. $\sigma_{i,t}$ is the average daily stock return volatility of firm i in year t in columns (1) and (3), and the annual abnormal volatility (based on the Fama-French three-factor model) in columns (2) and (4). The controls $X_{i,t}$ include Q (market value of assets/book value of assets), book leverage, cash holdings (normalized by book assets), EBITDA (normalized by lagged book assets), and size (log book assets) at the end of year t, as well as the level of average daily stock returns in year t and its interaction with λ_i. In Panel B, the outcome variable is capital expenditures (normalized by lagged net PPE) in columns (1) and (2), annual percentage change in inventory in columns (3) and (4), and annual percentage change in employment in columns (5) and (6). The independent variables are the same as those in Panel A. Firm and industry-year fixed effects are included. R^2 does not include fixed effects. The sample is Compustat firms from 1985 to 2018. Standard errors clustered by industry (two-digit SIC) and year are presented in parentheses. *** $p = 1\%$, ** $p = 5\%$, * $p = 10\%$.

versus 100%. Our results align with theoretical predictions and indicate that asset specificity is crucial to the negative effects of uncertainty on firm investment.

In Table VI, Panel A, columns (3) and (4) we study inventory investment, which can also play an important role for economic fluctuations (see Ramey and West 1999 for a summary). Here we use the inventory liquidation recovery rate for λ and interact it with the uncertainty measure σ. We find that higher uncertainty is also associated with significant reductions in inventory investment when the inventory liquidation recovery rate is low, but not when the inventory recovery rate is high. Again, the response to uncertainty is roughly zero if inventory is fully generic (i.e., when the inventory liquidation recovery rate is one).

Furthermore, in Table VI, Panel B, we find that the impact of uncertainty on fixed-asset investment is affected by PPE liquidation recovery rates, but not by inventory liquidation recovery rates. Conversely, the impact of uncertainty on inventory investment is affected by inventory liquidation recovery rates, but not by PPE liquidation recovery rates. In other words, among fixed assets and inventory, there is a clear mapping between the specificity of one type of asset and its investment sensitivity to uncertainty. In Panel B, columns (5) and (6), we examine employment growth as the outcome variable. We observe that higher uncertainty also has a negative effect on employment growth. This negative effect is smaller when PPE liquidation recovery rates are higher, although the statistical significance is weaker for this interaction. To the extent that employees have complementarity with plants and equipment, the specificity of fixed assets may also have some effect on the sensitivity of employment growth to uncertainty.

We perform several robustness checks in Table VII. In column (1), we use the PPE liquidation recovery rate at the three-digit SIC code level. The result is similar to that in Table VI using the PPE liquidation recovery rate at the two-digit SIC code level. In column (2), we use the PPE liquidation recovery rate (at the two-digit SIC code level) predicted by physical attributes in Table IV, Panel A, column (1). This variable produces a larger coefficient for the interaction with volatility; its stronger effect could possibly arise from less measurement noise. In column (3), we use the average PPE liquidation recovery rate calculated using a randomly selected half of the cases for a two-digit SIC code, and instrument it with the average PPE liquidation recovery rate calculated using the other half of the cases (we use industries with more than five

TABLE VII

Robustness Checks for Investment Response to Uncertainty

	CAPX investment rate			
	(1)	(2)	(3)	(4)
Vol	− 2.22***	− 3.59***	− 3.02***	− 2.28***
	(0.25)	(0.22)	(0.76)	(0.32)
Vol × PPE liquidation recovery rate (3-digit)	1.48**			
	(0.66)			
Vol × Predicted PPE liquidation recovery rate		5.98***		
		(0.94)		
Vol × PPE liquidation recovery rate (random half)			4.19*	
			(2.38)	
Vol × PPE liquidation recovery rate				2.48**
				(1.08)
Net PPE/assets				− 0.86***
				(0.12)
Vol × Net PPE/assets				− 0.39
				(0.77)
Controls	Yes			
Fixed effect	Firm, industry-year			
Observations	79,058	104,505	78,537	103,832
R^2	0.08	0.08		0.12

Notes. This table presents firm-level annual regressions on how the investment response to uncertainty varies with asset specificity: $Y_{i,t+1} = \alpha_i + \eta_{j,t} + \beta\sigma_{i,t} + \phi\lambda_i \times \sigma_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$. The outcome variable $Y_{i,t+1}$ is capital expenditures (normalized by lagged net PPE). $\sigma_{i,t}$ is the average daily stock return volatility of firm i in year t. In column (1), λ_i is the average PPE liquidation recovery rate in the three-digit SIC industry. In column (2), λ_i is the PPE liquidation recovery rate predicted by physical attributes from column (1) of Table IV, Panel A. In column (3), λ_i is the average PPE liquidation recovery rate in each two-digit SIC code using a randomly selected half of the cases, instrumented by the average PPE liquidation recovery rate in each two-digit SIC code using the other half; we use industries with over five cases with liquidation recovery rate data. In column (4), λ_i is the average PPE liquidation recovery rate in the two-digit SIC industry, and we also control for the book value of PPE at the end of year t (normalized by total assets) as well as its interactions with volatility and with the level of stock returns in year t. Other control variables are the same as those in Table VI. Firm and industry-year fixed effects are included. R^2 does not include fixed effects. The sample is Compustat firms from 1985 to 2018. Standard errors clustered by industry (two-digit SIC) and year are presented in parentheses. *** $p = 1\%$, ** $p = 5\%$, * $p = 10\%$.

observations of PPE liquidation recovery rates in our liquidation analysis data set). This design may also reduce measurement noise, and we find a larger coefficient for the interaction with volatility as well. In column (4), we run the same regression as that in column (1) of Table VI, Panel A, but also control for the book value of PPE and its interactions with the second moment (volatility) and the first moment (the level of stock returns). This check shows that the specificity (irreversibility) of fixed assets is distinct from the amount of fixed assets. We observe that a higher PPE liquidation recovery rate reduces the negative impact of volatility on investment spending (as before), whereas the amount of PPE does not have a significant interaction with volatility. Finally, we perform robustness checks using quarterly data in Online Appendix Table 7: we repeat the baseline tests in Table VI, Panel A together with the tests in Table VII, except that the outcome variable is the quarterly investment rate and volatility and control variables are also measured every quarter. We find similar results; the magnitude of the results in the quarterly regressions is slightly smaller as investment decisions may take time to implement (Lamont 2000).

3. *Investment Sensitivity to Demand.* Previously we included the first moment as a control and focused on the sensitivity of investment to the second moment. Guiso and Parigi (1999) point out that higher uncertainty (the second moment) can also weaken the response of investment to demand (the first moment), and this effect should be stronger when investment irreversibility is stronger. As they write, with irreversible investment, "the demand threshold that triggers investment rises with uncertainty." When uncertainty is high, a firm can be more hesitant to invest following a positive shock in case good prospects do not materialize, especially if investment is irreversible. In Online Appendix Table 8, we follow the empirical framework in Guiso and Parigi (1999), Table IV and estimate the following regression for firms with high and low asset specificity (a PPE liquidation recovery rate in the bottom and top terciles, respectively):

$$(4) \qquad Y_{i,t+1} = \alpha + \phi\sigma_{i,t} \times \mu_{i,t} + \theta\sigma_{i,t} + \xi\mu_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}.$$

As before, the outcome variable $Y_{i,t+1}$ is the investment rate in year $t + 1$. The key independent variables are the second moment $\sigma_{i,t}$ (measured using the volatility of stock returns) and its interaction with the first moment $\mu_{i,t}$ (measured using the level of stock returns). Like Guiso and Parigi (1999), we perform the regression in equation (4) for firms in industries with high and low asset specificity, that is, PPE liquidation recovery rates in the bottom and top terciles. The key prediction is that the interaction coefficient ϕ should be more negative when asset specificity is higher. Online Appendix Table 8 shows that this is the case.

Taken together, the empirical findings align closely with theories of investment irreversibility. In the data, the negative impact of uncertainty on investment depends strongly on the specificity of each type of asset, and it dissipates if assets are fully generic.

IV.B. Economic Effect of Intangible Assets

Classic investment theories have focused on investment in fixed assets (or "tangible" capital). Recent research documents that a key development in recent decades is the growing importance of intangible assets (Corrado, Hulten, and Sichel 2009; Peters and Taylor 2017; Haskel and Westlake 2018; Crouzet and Eberly 2019, 2021b), broadly defined as production assets without physical presence. Intangible assets include identifiable components such as computerized information (software, data), usage rights (licenses, excavation rights, route rights, etc.), patents and technologies, and brands, which are separable and transferable to alternative users on a standalone basis (Mann 2018; Ma, Tong, and Wang 2021). They also include organizational capital, firm-specific human capital, and other forms of "economic competencies" (Corrado, Hulten, and Sichel 2005), which are not necessarily independently identifiable or separable from the firm.

What is the fundamental difference between physical and intangible assets? A major concern in recent research is that rising intangibles could deplete firms' liquidation values (Giglio and Severo 2012; Caggese and Pérez-Orive 2022; Falato et al. forthcoming). In this section, we show that our data provides new insights for understanding this issue. In particular, we document that the rise of intangible assets so far has not had a first-order impact on firms' liquidation values, contrary to conventional wisdom.

As mentioned already, intangible capital includes different sets of nonphysical assets. To analyze intangible assets, we first lay out the main categories of intangible assets and explain their measurement. In particular, only a subset of intangible assets are currently reported among firms' assets in financial statements, which are often referred to as book intangibles. For book intangibles, we can obtain their quantity (net book values), and we have data on their liquidation recovery rates. Book intangibles have two components:

- $Intan_{book,separable}$: this category includes identifiable intangible assets acquired from outside, such as licenses, patents, customer data, and trade names. These assets cover all book intangibles except goodwill (discussed below). We observe their liquidation recovery rates in our data. Three-quarters of the cases in our data report the liquidation recovery rate of nongoodwill intangibles separately, and one quarter only report the combined liquidation recovery rate of all book intangibles. In the latter situation, we estimate the liquidation recovery rate of nongoodwill intangibles as the combined liquidation recovery rate divided by the share of nongoodwill intangibles in book intangibles in the industry (goodwill generally has no liquidation value, as explained below).

- $Intan_{book,nonseparable}$: this category includes goodwill (which comes from the difference between the amount a firm paid to acquire a target firm and the book value of the target firm's assets). The liquidation value of goodwill is deemed to be zero because goodwill typically represents the value of synergies between the acquirer and the target, or organizational capital of the target. Our data also always report zero liquidation value for goodwill.

Other intangible assets are not reported in firms' financial statements (not "capitalized"). Their quantity is challenging to measure, and several studies provide aggregate estimates for the national accounts or firm-level estimates for Compustat (Corrado, Hulten, and Sichel 2009; Eisfeldt and Papanikolaou 2013; Peters and Taylor 2017).[22] For our purposes, conceptually we think about two groups of off balance sheet intangibles.

- $Intan_{nonbook,separable}$: this category includes intangible assets that are not reported on firms' balance sheets but are potentially separable, such as internally developed technologies or brands. They may have positive liquidation values if they can exist separately from a given firm and can be sold to other firms. The amount of such

22. In terms of magnitude, total nongoodwill book intangibles among Compustat firms are about 60% of total intangibles in national accounts (intellectual property products reported by the BEA). At the BEA sector level, the ratio of $\frac{\text{nongoodwill book intangibles}}{\text{nongoodwill book intangibles + net PPE}}$ in Compustat is 0.5 correlated with the ratio of $\frac{\text{intangibles}}{\text{intangibles + fixed assets}}$ in BEA data, and the average difference is 0.05. Total nongoodwill book intangibles in Compustat have about the same magnitude as Peters and Taylor (2017)'s estimate of "knowledge capital" among Compustat firms (based on capitalizing R&D spending), and they are about 60% as large as Peters and Taylor (2017)'s estimates of "organizational capital" (based on capitalizing 30% of selling, general, and administrative expenses).

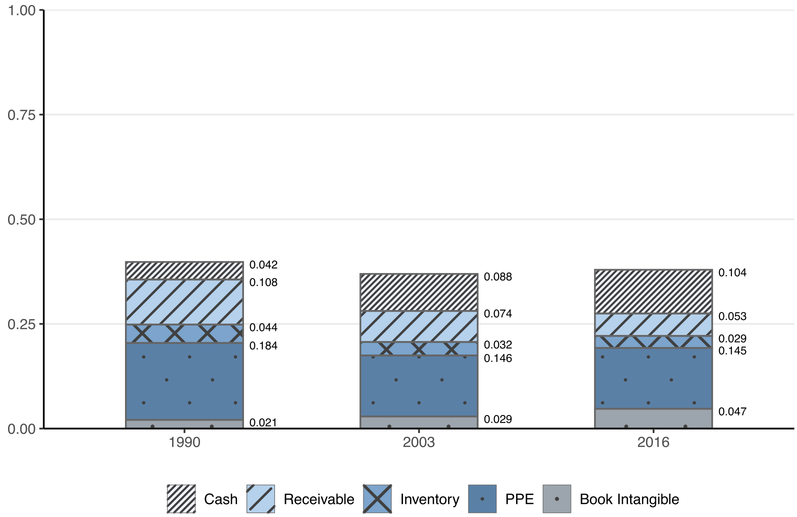


FIGURE II

Liquidation Value over Time (Compustat Aggregate)

This figure shows the estimated total liquidation value from cash, working capital (receivable and inventory), PPE, and book intangible among all Compustat firms for three example years. Total liquidation value is normalized by total book assets. The numbers represent the liquidation value from each asset category.

intangible assets is difficult to measure, and we assign zero liquidation values to them to be conservative.

- $Intan_{nonbook,nonseparable}$: this category includes intangibles that are not separable from a given firm, such as organizational capital. We also assign zero liquidation value for this category.

We present an overview of the impact of rising intangibles on firms' liquidation values in Figure II. We show the estimated liquidation value of all Compustat firms (as a share of total book value) for three example years (1990, 2003, and 2016) over the sample period in Crouzet and Eberly (2019). Liquidation values include those from (nongoodwill) book intangibles, PPE, working capital, and cash. As explained already, we assume all other types of intangible assets have zero liquidation value to be conservative. Accordingly, our results provide a lower bound for the liquidation value of intangibles. Online Appendix Figure 1 shows that the results are similar if we add nonbook intangibles estimated by

Peters and Taylor (2017) to total assets, and assume zero liquidation value for all nonbook intangibles to be conservative.

Figure II shows that the estimated liquidation value from PPE declined slightly over this period (by about 4% of book assets), which is partly offset by an increase in the liquidation value of book intangibles. Meanwhile, firms have less receivables and more cash. Overall, total liquidation values do not seem to change drastically, although by many measures the prevalence of intangibles has increased substantially over this period (e.g., aggregate book intangibles increased from 6% of total assets to 26%). Indeed, the sum of liquidation values from PPE and book intangibles has stayed roughly constant at around 20% of the book value of assets.

We then explain several reasons that contribute to the stability of firms' liquidation values even though intangible assets have increased substantially. First, physical assets are already highly specific in many industries (e.g., the average industry-level liquidation recovery rate for PPE is 35%). From 1990 to 2016, the share of PPE in total assets among Compustat firms declined by 12.5%. Even if all intangible assets had zero liquidation value, the decline in PPE would reduce total liquidation values by less than 4% of book assets.

Second, at least for identifiable book intangibles ($Intan_{book,separable}$), their liquidation recovery rates are not necessarily much lower than those of PPE (e.g., transferring intangibles does not incur transportation costs). The increase in this group of intangible assets alone raises total liquidation values by around 3% of book assets, partly offsetting the decline of the liquidation value of fixed assets. For further illustration, Figure III plots the average liquidation recovery rate of PPE and that of book intangibles for Fama-French 12 industries (except finance). For each industry, the three bars represent the average liquidation recovery rate of PPE, book intangibles, and nongoodwill book intangibles, respectively. We see that the second bar and especially the third bar are not much lower than the first bar. For two-digit SIC industries, the mean industry-level liquidation recovery rate of nongoodwill book intangibles is about 32%, and the interquartile range is 4.5%–42%. Indeed, these values are comparable to PPE liquidation recovery rates on average, but with more dispersion.[23] In sum, identifiable intangibles can

23. Several factors can be relevant to put the liquidation recovery rates of book intangibles in perspective. First, given the eligibility criteria of book intangibles

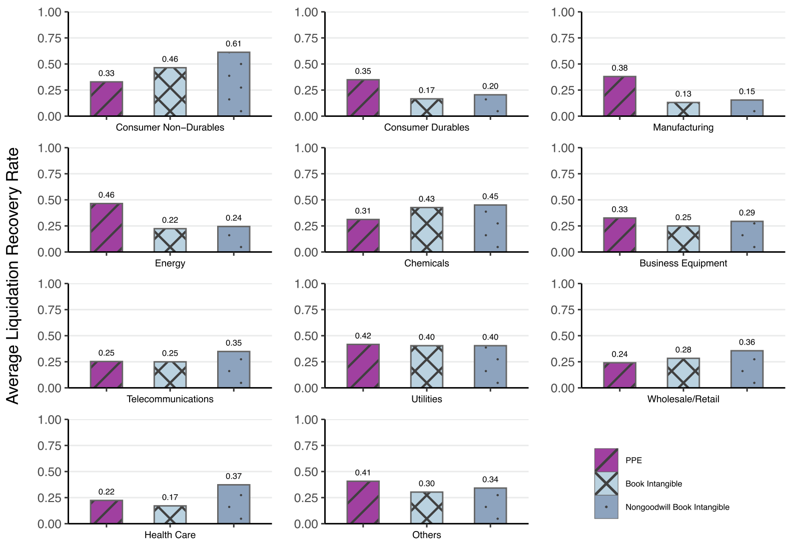


FIGURE III

Industry-Average Liquidation Recovery Rate: PPE and Book Intangibles

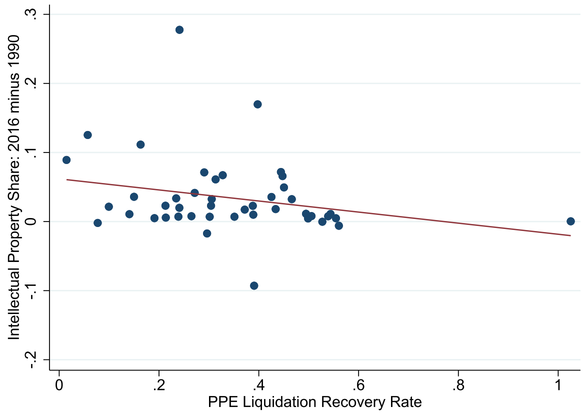
This figure shows the liquidation recovery rate of PPE and book intangibles in Fama-French 12 industries (except financials). For each industry, the first bar shows the average liquidation recovery rate of PPE. The second bar shows the average liquidation recovery rate of book intangibles. The third bar shows the average liquidation recovery rate of nongoodwill book intangibles.

obtain liquidation values on their own and are not necessarily more specific than tangible assets such as PPE.

Third, we also find that the rise of intangibles in recent decades has been especially pronounced in industries where physical assets are more specific. We use two common measures of the stock of intangibles. One is the BEA's estimate of the stock of intellectual property for each BEA industry. Another is Peters and Taylor (2017)'s estimate of the stock of intangibles for Compustat firms, which combines book intangibles with the estimated stock of off-balance-sheet intangibles. Figure IV plots the change in the industry-level share of intangible assets relative to the sum of

(i.e., acquired from external parties), these intangible assets may be easier to trade and therefore have higher liquidation recovery rates. Second, the market for trading intellectual properties and other identifiable intangibles (various types of rights) is developing over time (Mann 2018), so intangibles' liquidation recovery rates may further improve in the future as markets develop and mature.

(A) Industry-Level Intellectual Property Assets (BEA)



(B) Firm-Level Intangible Assets (Compustat)

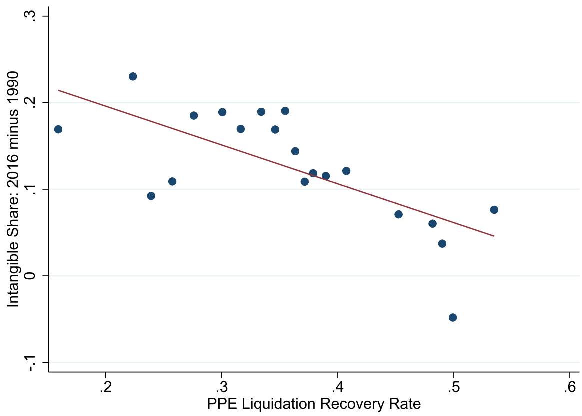


FIGURE IV

Specificity of Fixed Assets and Rising Intangibles

This figure shows binscatter plots of the rise of intangibles by the level of the PPE liquidation recovery rate. Panel A uses BEA data on intellectual property assets in each BEA industry to measure intangible assets. The y-axis is the change in intellectual property as a share of intellectual property plus fixed assets from 1990 to 2016, and the x-axis is the average PPE liquidation recovery rate in each BEA industry. Panel B uses Peters and Taylor (2017)'s estimate of total capitalized intangibles (including book intangibles, capitalized R&D, and capitalized value of 30% of selling, general, and administrative expenses) for each Compustat firm to measure intangible assets. The y-axis is the firm-level change in capitalized intangibles as a share of capitalized intangibles plus net PPE from 1990 to 2016, and the x-axis is the PPE liquidation recovery rate of the firm based on its industry.

fixed assets and intangibles from 1990 and 2016 (y-axis) against industry-level PPE liquidation recovery rates (x-axis). Online Appendix Table 9 shows the results in regressions, using both the PPE liquidation recovery rates directly and the values predicted by physical attributes. The data suggest that the shift from physical assets to intangibles has been stronger where the liquidation values of fixed assets are already small and there is not much to "lose" further. However, the impact of this mechanism has been small in magnitude (even if the decline of fixed assets in all industries is set to be the mean level, results in Figure II differ by less than 1 percentage point).

Taken together, our data shows that rising intangibles may not substantially reduce firms' liquidation values. Accordingly, it is unclear that the primary effect of this development is tighter borrowing constraints due to lower liquidation values. Furthermore, in the United States, firms' debt capacity is not necessarily tied to liquidation values, especially when firms have positive earnings (Lian and Ma 2021; Kermani and Ma 2022b). Indeed, as intangible assets become more prevalent over time, the leverage among U.S. nonfinancial firms has been rising rather than falling (Graham, Leary, and Roberts 2015). Similarly, our results suggest that investment irreversibility or sunkness may not increase significantly with rising intangibles. Some identifiable intangibles such as licenses, data, and patents can be sold off and are partially reversible (while many fixed assets have high irreversibility, too).

What, then, is different about intangibles? One possibility is that intangibles can be more scalable (Haskel and Westlake 2018; Crouzet and Eberly 2019). For instance, because intangibles are nonphysical and not bound by particular locations, they can be used at multiple places simultaneously (e.g., enterprise planning systems, brands, data). Greater scalability provides advantages to large firms (Autor et al. 2020; Hsieh and Rossi-Hansberg 2021; Kwon, Ma, and Zimmermann 2022; Lashkari, Bauer, and Boussard 2022). In addition, intangible assets raise a number of questions about the proper measurement of economic activities such as growth, investment, and productivity (Corrado, Hulten, and Sichel 2005; Brynjolfsson, Rock, and Syverson 2021; Crouzet and Eberly 2021a, 2021b). These areas are likely to be more central for the difference between intangible assets and physical assets.

IV.C. Other Implications

In this section, we briefly summarize several other applications of our data. Future work can further explore these or other implications.

1. *Productivity Dispersion.* Several studies suggest that investment irreversibility can affect productivity dispersion (Eisfeldt and Rampini 2006; Lanteri 2018). Using Q dispersion as a proxy for the dispersion in the productivity of capital, Online Appendix Figure 2 presents evidence in line with this view. In industries with lower average firm-level liquidation value of PPE and working capital (normalized by total book assets), we observe higher average annual dispersion in Q. We use both regular Q (market value of assets over book value of assets) in Panel A and Q accounting for the impact of intangibles (Peters and Taylor 2017) in Panel B. Online Appendix Table 10 presents corresponding regressions. It also shows that this relationship is significant among large (total assets above median in Compustat each year) and small firms; this result suggests that the relationship is not driven by borrowing constraints tied to liquidation values, which are less relevant for large firms (Lian and Ma 2021; Kermani and Ma 2022b).

2. *Price Rigidity.* Woodford (2005) and Altig et al. (2011) point out that when capital is firm-specific (instead of generic and available from an economy-wide rental market), firms can display higher price stickiness. We collect information on industry-level price rigidity using the frequency of price changes from Nakamura and Steinsson (2008) and Gorodnichenko and Weber (2016).[24] Given that in practice PPE and inventory are both relevant for production, in Online Appendix Table 11 we investigate each of them, as well as the combined measure of the total liquidation value from PPE and working capital (normalized by book

24. As Altig et al. (2011) explain, when a firm considers raising prices, it understands that a higher price implies less demand and less output; if the capital stock is costly to adjust, the firm would be left with excess capital, which can decrease its incentive to increase prices in the first place. In this model with Calvo pricing, the magnitude of price change is affected. In the data, what is typically measured is instead the frequency of price change. Small changes in desired prices in practice may translate to no price change if there are fixed costs of price changes as in menu cost models.

assets). Online Appendix Figure 3 also shows that price stickiness is higher in industries with lower average firm-level liquidation value of PPE and working capital (normalized by total book assets).

3. *Boundaries of the Firm.* A long-standing observation is that firms are more exposed to holdup problems by suppliers and customers when they need to invest in assets with high specificity (Klein, Crawford, and Alchian 1978; Williamson 1979; Grossman and Hart 1986).[25] Legal institutions that safeguard contract enforcement alleviate these problems (La Porta et al. 1998; Nunn 2007). When the rule of law is weak, vertical integration can be more important. We measure the degree of vertical integration across countries and industries using data from ORBIS. Following the methodology in prior work (Fan and Lang 2000; Acemoglu, Johnson, and Mitton 2009; Alfaro et al. 2016), for each firm we construct a score ($S1$) that captures the extent to which it owns subsidiaries in upstream industries and a score ($S2$) that captures the extent to which it owns subsidiaries in downstream industries.[26] We take the average value of $S1$ and $S2$ for each pair of country and parent industry (four-digit BEA code). Finally, we use the liquidation recovery rate of fixed assets in our data matched to the parent's industry.[27] We use the rule of law index for each

25. The holdup problem can happen because of the specificity of production assets (e.g., PPE) or because of the specificity of trading relationships (e.g., whether the product is generic). Our data focus on the first dimension: for a given level of the specificity of the product, higher specificity of production assets will make the holdup problem more severe. For a subset of the industries, we can use the data from Rauch (1999) (which codes whether a commodity is exchange traded) as a proxy for the specificity of the product. In the data, this measure is not correlated with the specificity of PPE.

26. For instance, if producing \$1 of output in chemical manufacturing requires \$$x$ of oil and gas extraction input, then the "upstreamness" of an oil and gas extraction subsidiary owned by a chemical manufacturer is x. If producing \$1 of output in pharmaceutical manufacturing requires \$$y$ of chemical manufacturing input, then the "downstreamness" of a pharmaceutical manufacturing subsidiary owned by a chemical manufacturer is y. The variable $S1$ ($S2$) is the sum of the "upstreamness" ("downstreamness") of subsidiary industries that a parent firm has, computed using the 2012 BEA input-output tables (because its industry classifications are closest to the 2017 NAICS codes in ORBIS). We use the "All Subsidiaries First Level" data set from ORBIS and restrict to parents in nonfinancial industries.

27. Because our liquidation recovery rate data are based on U.S. firms, this matching assumes that firms in the United States have a limited degree of vertical integration, which is indeed the case based on the vertical integration scores. For

country from the World Bank Governance Indicators as a proxy for contract enforcement (this variable has zero mean and unit variance).

In Online Appendix Table 12, we find that weaker rule of law is associated with more vertical integration for firms in high asset specificity industries, whereas this effect is not present among low asset specificity industries. We control for the capital intensity (the share of fixed assets in total assets) and the external-finance dependence of an industry (Rajan and Zingales 1995), as well as the interactions of these variables with the rule of law in subsequent columns. These controls indicate that the impact of legal environments depends more on the specificity of assets, not just the quantity of assets (the traditional capital intensity measure). We also control for log real GDP per capita (in U.S. dollars) and the business sophistication index from the World Economic Forum Global Competitiveness Report (which controls for the costs of running large integrated companies whereas rule of law modulates the benefits from vertical integration). In columns (3), (4), (7), and (8), we further add country and industry fixed effects to account for other factors that encourage or impede vertical integration (e.g., management sophistication or regulation) in a country or in an industry (Holmstrom and Roberts 1998; Joskow 2008). In columns (4) and (8), we instrument the liquidation recovery rates of fixed assets using the physical attributes discussed in Table IV, Panel A, column (1). As noted by Klein (2008), due to the lack of systematic data on asset specificity, previous empirical analyses of its impact have largely focused on examples in particular industries. Our data provide a potential avenue to test these insights more systematically.

V. Connections to Model Parameters

Finally, we summarize the connection between our findings and the parameters used in two common classes of models.

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parsimony, our vertical integration measure abstracts away from vertical linkages among subsidiaries that are not related to the parent. We also focus on the case where the parent (the main industry) has specific assets and therefore acquires upstream or downstream firms, instead of the case where a firm acquires a supplier or a customer because the subsidiary firm has specific assets (since in this case the empirical design is much less straightforward).

V.A. *Models of Investment Irreversibility*

Models of investment irreversibility often calibrate or estimate the loss from disinvestment of capital. In particular, this class of models specifies that firms spend I^+ when they invest, and receive λI^- when they disinvest, where λ denotes the fraction of the purchase price of capital that firms can recover from disinvestment (Abel and Eberly 1996; Bloom 2009). Accordingly, λ has the same unit as the liquidation recovery rate in our data. Bloom (2009) estimates the loss from disinvestment to be 43%, which translates into a liquidation recovery rate λ of 57%. Lanteri (2018) estimates the equilibrium loss from disinvesting used capital to be around 7% (i.e., λ as high as 93%). Our data, like Ramey and Shapiro (2001), imply larger losses from disinvesting fixed assets on a standalone basis.

Our data also suggest that the losses from disinvestment can vary substantially across industries. In this case, whether shocks hit industries with high versus low asset specificity can lead to different implications. For instance, the COVID-19 shock generated significant shortages of certain products, and such shortages can be more severe if the sectors affected by the shock require assets with high specificity. When irreversibility is high, firms can be less willing to ramp up investment when product shortages occur, especially if demand shocks are temporary. The recurring shortages following the COVID-19 crisis are in line with the observation that asset specificity can contribute to inefficient allocation of productive resources across different sectors in the economy (Caballero and Hammour 1998).[28]

Overall, our findings suggest that if capital reallocation takes the form of directly selling fixed assets on a standalone basis, the loss can be significant. The loss could be smaller if reallocation takes the form of mergers and acquisitions, which transfer not just fixed assets but also human and organizational capital.[29] However, adjustments through mergers and acquisitions are lumpy and difficult to implement if a firm simply wants to downsize its

28. Correspondingly, in multisector models such as Baqaee and Farhi (2022), a useful statistic could be the correlation between the degree of asset specificity and the demand shocks across industries.

29. For instance, targets in mergers are often bought at a premium relative to premerger market value (Mulherin, Netter, and Poulsen 2017); firms acquired out of Chapter 11 bankruptcy also have sale values comparable to going-concern values in traditional reorganizations.

capital stock. Accordingly, high asset specificity inevitably limits firms' flexibility to disinvest and downsize.

V.B. Models of Financial Frictions

A number of papers impose financial frictions in the form of "collateral constraints" for borrowing: firms need to pledge physical capital to borrow, and debt capacity is limited by the liquidation value of the assets pledged (Kiyotaki and Moore 1997).[30] In other words, firms' borrowing b is restricted by the liquidation value of the capital stock K, $b \leqslant \lambda K$, where λ is then the liquidation recovery rate. Although this form of borrowing constraint may not be first order among major nonfinancial firms in the United States, it is more prevalent among small firms and firms with negative earnings, and models may find liquidation value data relevant in these settings (Lian and Ma 2021; Kermani and Ma 2022b).

Models of traditional collateral constraints have used a variety of calibrated or estimated parameters for λ. The parameters in Moll (2014) and Midrigan and Xu (2014) indicate that firms can borrow around 80% of the book value of fixed assets. The estimates in Catherine et al. (2022) imply that firms can only borrow around 15%–20%, which are close to the PPE liquidation recovery rates in our data. The main reason for the different parameters seems to be that the former set of papers match the total leverage of firms, whereas Catherine et al. (2022) obtain the estimate from the sensitivity of borrowing to real estate value. Based on the findings from Lian and Ma (2021), when models target total debt, a sizable portion of the debt can be cash flow–based lending (i.e., lending on the basis of firms' cash flow value from operations) instead of asset-based lending (i.e., lending on the basis of the liquidation value of separable assets such as PPE). Correspondingly, total borrowing may not necessarily reflect the tightness of traditional collateral constraints, and models that target the sensitivity of borrowing to real estate value are more likely to infer how much firms can borrow from pledging fixed assets (Catherine et al. 2022).

30. We use "collateral constraints" in quotation marks to refer to the common academic use of the term, where "collateral" typically implies tangible assets that creditors can seize and liquidate. In practice, collateral under U.S. law takes many forms, including the firm as a whole (e.g., blanket liens), where the function is to provide creditors with priority rather than tangible assets that they intend to seize.

Several macro-finance analyses also feature models of default risks, such as Khan, Senga, and Thomas (2020) and Ottonello and Winberry (2020). In these models, when a firm defaults, lenders recover a fraction of its capital. Our data on liquidation values can inform what can be obtained if firms liquidate. However, in the United States many firms (e.g., the vast majority of public firms) restructure upon default (rather than liquidate) and continue their business operations. For firms that restructure, lenders' payoffs are given by their going-concern values as operating businesses. For instance, in our data, the going-concern value is twice as large as the total liquidation value for the median Chapter 11 firm. Indeed, U.S. bankruptcy laws emphasize restructuring in large part because of the view that firms' going-concern values are much higher than liquidation values; the restructuring-based bankruptcy system is also important for the availability of cash flow–based debt. In other words, the low liquidation value (high specificity) of production assets underlies the development of legal infrastructure that helps preserve firms' going-concern values and enhances their ability to pledge cash flows; these features are important for understanding corporate debt contracts in practice.

Overall, in the United States, firms pledge physical assets for a subset of corporate debt contracts (asset-based debt in Lian and Ma 2021 and Kermani and Ma 2022b), where borrowing constraints as well as lenders' payoffs in default (Chapter 7 and Chapter 11) are primarily given by the liquidation value of the particular assets pledged. According to lenders, common debt limits for asset-based debt against industrial PPE are 20%–30% of the book value, similar to the average PPE liquidation recovery rate of 35% in our data. Therefore, for models where firms can only borrow against the liquidation value of fixed assets, our data suggest that debt capacity is rather limited. Nonetheless, firms in the United States can also borrow cash flow–based debt (where borrowing constraints are based on firms' operating earnings) and can restructure upon default (where total payoffs to lenders are given by firms' going-concern values from continuing operations). We investigate these issues in detail in Kermani and Ma (2022b) and show that preserving firms' going-concern values through creditor monitoring and restructuring helps firms borrow much beyond their liquidation values without significant costs for lenders.

VI. Conclusion

Asset specificity plays a key role in many lines of economics research. Obtaining systematic measures of the degree of asset specificity across industries has been a long-standing challenge. We tackle this challenge by constructing a new data set on the liquidation values of nonfinancial firms' assets, covering the main categories of assets on firms' balance sheets and all major industries. We quantify the degree of asset specificity using the liquidation recovery rate (i.e., liquidation value over book value), and document its variations across industries. We then investigate the key determinants of asset specificity. We show that the physical attributes of assets used in different industries have strong explanatory power for both the level and the cross-industry variations of asset specificity. We also examine the influence of time-varying industry conditions.

Finally, our new data illuminate several leading implications of asset specificity. We show that the degree of asset specificity explains firms' investment behavior, including the prevalence of disinvestment and the response to uncertainty. The findings provide direct empirical evidence that asset specificity is essential to the impact of uncertainty, and the negative effects of uncertainty are absent if assets are generic. We also shed light on the economics of intangible capital and demonstrate that the first-order effect of intangible assets is not necessarily to reduce firms' liquidation values. Taken together, we hope the data and analyses inform our understanding of the nature of firms' assets and its wide-ranging effects.

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Supplementary Material

Supplementary material is available at the *Quarterly Journal of Economics* online.

Data Availability

Data and code replicating the tables and figures in this article can be found in Kermani and Ma (2022a) in the Harvard Dataverse, https://doi.org/10.7910/DVN/FZGQBX.

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