Asset Specificity of Non-Financial Firms*

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Abstract

We develop a new dataset to study asset specificity among non-financial firms. The data covers the liquidation values of all major types of assets across industries. For the determinants of asset specificity, we show that assets' physical attributes (e.g., mobility, durability, and customization) play a crucial role; macroeconomic and industry conditions have the most impact when assets are not custom designed. We then investigate three implications of asset specificity. First, consistent with theories of investment irreversibility, high asset specificity is associated with less disinvestment, stronger investment response to uncertainty, and greater sensitivity of capital formation across countries to macroeconomic volatility. Second, the increasing prevalence of intangible assets has not significantly reduced firms' liquidation values, but intangibles appear more scalable. Third, firms have more vertical integration in countries with weaker rule of law when asset specificity is high.

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1 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, 2018) and magnify the impact of uncertainty (Bloom, 2009). Low liquidation values can also influence organizational structures (Williamson, 1981; Grossman and Hart, 1986) and financial contracts (Shleifer and Vishny, 1992; Hart and Moore, 1994).

While 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 in order 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, direct analyses of asset specificity have been difficult outside certain industries; models have also used a wide range of parameter values for the degree of asset specificity.

In this paper, we build a new dataset that directly measures the liquidation values of firms' assets across all major industries and asset categories (fixed asset, inventory, etc.). 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.[2] We then use this data to investigate both the determinants and the implications of asset specificity. The data reveals that physical attributes (e.g., mobility, durability, customization) account for both the overall level of asset specificity and the substantial differences across industries. Macroeconomic and industry conditions, in turn, have the most influence when assets are not custom designed. The data also provides novel evidence for understanding the consequences of investment irreversibility, the impact of intangible assets, and the prevalence of vertical integration around the world,

[1] Studies of particular assets include Ramey and Shapiro (2001) for aerospace manufacturing equipment, Pulvino (1998), Gavazza (2011), and Franks, Seth, Sussman, and Vig (2021) for aircraft, 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), Kim and Kung (2017), among others. Indeed, some work associated more fixed assets (higher tangibility) with higher redeployability, while others associated it with greater sunk costs and lower redeployability.

[2] For example, this measure corresponds to the degree of investment irreversibility in Bloom (2009) and the per-unit liquidation value of capital in Kiyotaki and Moore (1997). We discuss connections with model parameters in Section 5. 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 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 larger than one), this alternative ratio could be lower.

illuminating traditional types of investment, new forms of capital, and boundaries of firms.

To collect the liquidation recovery rates for major types of assets across industries, we use systematic disclosures of this information from US Chapter 11 filings between 2000 and 2016. 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 were to be liquidated (over a roughly one-year time frame). This reporting covers *all* of firms' assets and provides detailed assessments for each financial statement category, such as property, plant, and equipment (PPE), inventory, etc. These liquidation value estimates commonly derive from specialist appraisers who perform on-site examinations and simulate live liquidations; they align with available auction results as we discuss below. 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.

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, and it ranges from about 70% for transportation services to less than 10% for personal services. The value for inventory is 44% on average, 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 both the Chapter 11 sample and 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, and three times as large for the median Compustat 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 is available. Specifically, the liquidation recovery rates are similar to auction results which cover equipment in aerospace manufacturing (Ramey and Shapiro, 2001) and construction. 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.

[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, as we show below. Accordingly, it is important for bankruptcy laws to preserve viable firms as operating businesses instead of liquidating them (Djankov, Hart, McLiesh, and Shleifer, 2008; Kermani and Ma, 2021).

[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).

We impute the average recovery rate from PPE sales among Compustat firms, which aligns with the average PPE liquidation recovery rate in our data. In addition, our data is in line with lenders' benchmarks for non-financial firms in general (e.g., 30% liquidation recovery rate for industrial PPE). 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. This data also performs well in explaining the investment decisions and organizational structures of firms across industries and countries.

After assembling the dataset, we analyze the determinants of asset specificity. We document the importance of physical attributes. For fixed assets in an industry, we measure three physical attributes: 1) mobility, using an asset's transportation costs (e.g., from producers to purchasers); 2) durability (as reallocation takes time), using depreciation rates; and 3) customization, using the amount of design costs in producing an asset. We construct these measures by collecting detailed information on the composition of fixed assets in an industry from the fixed asset table 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 table. We show that an industry's PPE liquidation recovery rate is lower when its assets are less mobile, less durable, and more customized. 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 depreciation, and no customization, the liquidation recovery rate would be around 100%. In other words, low liquidation values of production assets depend crucially on their specificity in location, time span, and usage (due to low mobility, low durability, and high customization, respectively). 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 macroeconomic and industry conditions affect variations of liquidation values over time. Consistent with Shleifer and Vishny (1992), liquidation values are higher under better macro and industry conditions. Interestingly, this relationship is weak on average but stronger when PPE is not custom designed. If assets are customized for a particular firm, they may not be useful to others in any case and economic conditions matter less; on the other hand, if alternative users are economy-wide or industry-wide, macro and industry conditions matter more. In terms of magnitude, if PPE is not customized, the liquidation recovery rate increases by three percentage points when real GDP growth is one percentage point higher; it increases by 0.6 percentage points when industry leverage is one percentage point lower. We find similar magnitudes using a large sample of construction equipment auctions. Correspondingly, variations in economic conditions do not easily change the overall picture of high asset specificity among non-financial firms, or offset the large differences across industries.

Asset specificity has a wide range of implications and we study three key 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 then 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, across countries, we find that macroeconomic volatility in an economy hampers fixed capital formation in industries with low PPE liquidation values, but not in industries with generic assets. These results suggest that macroeconomic stability can influence economic development (Ramey and Ramey, 1995), especially for industries with high asset specificity. Overall, the data shows a high degree of alignment with theoretical predictions, both qualitatively and quantitatively, and offers direct evidence that asset specificity is fundamental for disinvestment frictions and the effect of uncertainty. We also find evidence in line with other implications of irreversible investment, including productivity dispersion and price rigidity.

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; Crouzet and Eberly, 2019; De Ridder, 2019). 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; Caggese and Perez-Orive, 2018; Haskel and Westlake, 2018; Falato, Kadyrzhanova, Sim, and Steri, 2020). We find that the rise of intangibles has not led to a significant reduction in firms' liquidation values, for three reasons. First, physical assets such as PPE are already highly specific. Second, in many industries, the average liquidation recovery rates of separable intangibles are not necessarily lower than those of PPE (e.g., intangibles have no transportation costs). Third, the industries with greater increases in intangibles have been those with more specific PPE in the first place. Taken together, the aggregate liquidation value among Compustat firms (relative to their book value or market value) in 2016 is similar to that in 1996, even though the amount of intangibles increased substantially over this period (e.g., intangibles in firms' book assets rose from 9% to 26%). What then is different about intangibles? Although intangibles may not be distinct along the dimension of asset specificity, they appear more scalable. Since intangibles are non-physical, they are not bound by geographic locations and could be non-rival in a firm. We find that a higher prevalence of intangible capital such as knowledge capital is associated with higher employment and revenue shares of large firms, whereas asset specificity plays no such role.

Our last application studies the boundaries of the firm (Coase, 1937), where influential theories brought the issue of asset specificity to prominence. A key idea is that frictions such as holdup problems are more severe when production requires investment in specialized assets, which can favor organizing economic activities through firms rather than contracts (Klein, Crawford, and Alchian, 1978; Williamson, 1979; Grossman and Hart, 1986). Strong legal institutions safeguard contract enforcement and alleviate such problems (La Porta, Lopez-de Silanes, Shleifer, and Vishny, 1998; Nunn, 2007). When the rule of law is weak, however, vertical integration can be especially relevant. Our data on asset specificity, together with additional measures of firm structures (Acemoglu, Johnson, and Mitton, 2009; Alfaro, Conconi, Fadinger, and Newman, 2016), allows us to test these hypotheses across all major industries and over 100 countries. We find that when the rule of law is weaker and contracts are more challenging to enforce, firms in industries with high asset specificity (low PPE liquidation recovery rates) have a greater propensity to own subsidiaries in both upstream and downstream sectors. The interaction between asset specificity and rule of law remains when we include country and industry fixed effects (to account for other reasons for differences in vertical integration) as well as when we use PPE liquidation recovery rates predicted by physical attributes. In sum, our findings provide systematic evidence that the combination of asset specificity and contractual environments affects the boundaries of firms.

It is also natural to ask how asset specificity affects firms' debt contracts and borrowing capacity, which we study in a companion paper (Kermani and Ma, 2021). We find that liquidation values have a significant positive impact 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.

Finally, we connect our data to 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, Chaney, Huang, Sraer, and Thesmar, 2019). 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.

Literature Review. Our work makes three contributions for understanding the asset specificity of non-financial firms. First, we provide comprehensive data for all major types of assets across industries. A number of papers use liquidation values of certain types of assets (e.g., Ramey and Shapiro (2001), Benmelech, Garmaise, and Moskowitz (2005), among others), or indirect proxies across industries (e.g., Rajan and Zingales (1995), Almeida and Campello (2007), Bernstein, Colonnelli, and Iverson (2019), among many others). Our direct measurement is important for investigating the determinants of asset specificity, connecting to models, and interpreting the magnitude of the results. Our coverage across industries is crucial for studying several issues about the foundations and implications of asset specificity, and it helps demonstrate the results' broad applicability.

Second, we present systematic analyses of the foundations of asset specificity. Specificity due to physical attributes has been proposed since at least Williamson, but direct empirical evidence is sparse. We show that physical attributes including mobility, durability, and customization have substantial explanatory power for the liquidation values of assets in different industries.[5] Specificity due to market conditions highlighted by Shleifer and Vishny (1992) has been analyzed in prior work, primarily through the number and conditions of alternative users in the airline industry (Pulvino, 1998; Gavazza, 2011). We provide evidence across different industries and demonstrate that the impact of macro and industry conditions varies depending on customization (which shapes the scope of alternative users).

Third, we leverage the granular nature of the data to illuminate leading implications of asset specificity. We revisit the consequences of investment irreversibility (Pindyck, 1991; Caballero, 1999; Bloom, 2014), which was previously studied using indirect proxies (Gulen and Ion, 2016; Kim and Kung, 2017), and point to three new insights. Our direct measurement shows that the negative effects of uncertainty are absent when assets are fully generic, that investments in both fixed assets and inventory respond to uncertainty according to their respective specificity (which helps differentiate the irreversibility channel from alternative mechanisms), and that macroeconomic volatility in a country disproportionately affects high asset specificity industries. Moreover, we present novel evidence on the impact of intangible assets, which is an important open question for understanding the modern economy (Corrado, Hulten, and Sichel, 2005; Haskel and Westlake, 2018; Crouzet and Eberly, 2019). Finally, we document how asset specificity combined with contractual environments shapes vertical integration across industries and countries. As surveys by Joskow (2008) and Klein (2008) point out, since asset specificity is difficult to measure consistently across industries, empirical analyses of its effects have largely focused on single-industry case studies.

The rest of the paper is organized as follows. Section 2 explains the data collection and presents basic statistics. Section 3 studies the determinants of asset specificity. Section 4 investigates the implications of asset specificity. Section 5 summarizes the comparison with model parameters. Section 6 concludes.

[5] Several papers show that lower transportation costs facilitate commodities and assets to be traded more widely (Hummels, 2007; Ma, Murfin, and Pratt, 2020). We find that lower transportation costs are associated with significantly higher liquidation recovery rates.

2 Data and Basic Statistics

This section describes our data on asset specificity and our checks of its reliability. 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). By definition, high asset specificity means limited value in alternative use and correspondingly a low liquidation recovery rate. Finally, the liquidation recovery rate in our data shows the property of *each type of asset*; it 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.[6]

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 most firms have multiple types of assets). Second, the ratio of liquidation value to cost is, to a large extent, determined by the inherent attributes of assets used in an industry (as we further verify in Section 3), 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 as 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, which we discuss in more detail in Section 5. 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 2.4.

2.1 Data Collection

A key challenge for measuring the degree of asset specificity among non-financial 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 firms own, which comes from the liquidation analysis performed in Chapter 11 corporate reorganizations. In particular, firms in Chapter 11 continue to operate, but they are also required

[6] See Kermani and Ma (2021) for analyses of the default recovery rate of debt.

by law to document the estimated 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 roughly one year. The orderly liquidation value is different from the forced liquidation value, which refers to forced sales in a short period of time such as 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.

Specifically, we begin with a list of Chapter 11 filings by public US non-financial firms between 2000 (the start of electronic court filings) and 2016 from New Generation Research's BankruptcyData. We process the liquidation analysis in their disclosure statements, which we retrieve from Public Access to Court Electronic Records (PACER) and BankruptcyData.[7] 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, together with notes that explain the sources and assumptions of the estimates. Internet Appendix Table IA1 shows two examples of the summary tables, from Lyondell Chemical and Sorenson Communications. Internet Appendix Section IA2 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. We have been able to retrieve liquidation analysis summary tables for over 350 cases covering nearly 50 two-digit non-financial SICs.[8]

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).[9] 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

[7] When a case has multiple disclosure statements, we use the earliest version. If the information we need is not available in the first version, we then use the latest version.

[8] Table IA2 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 retail (less than 10 to 20 firms in Compustat). We have many observations for large industries such as business services and chemicals.

[9] For instance, Pulvino (1998) studies aircraft sales and finds that the transaction prices are 14 percent higher when the seller airline is financially unconstrained. This difference can reflect that different airlines have different reservation prices, which affect whether they agree to sell an aircraft (Pulvino, 1998). It can also arise from other strategic considerations in selecting which aircraft to sell (Franks et al., 2021).

comparisons across industries or asset types. Third, the data has a standardized format for firms across different industries and a convenient level of aggregation corresponding to each financial statement category, so it 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 provides 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 value (i.e., proceeds from asset sales) rather than net liquidation value (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. Overall, while the concept "asset specificity" refers to limited values in alternative use, it does not stipulate how assets should be sold (e.g., mandatory versus optional). Obtaining data to capture all forms of asset sales would be very challenging. The orderly liquidation value captured by our data is one measure which offers a simple, consistent metric across different types of assets and industries.

Finally, our data covers assets owned by firms. Firms may also use assets through operating leases, which were not reported on their balance sheets before 2019. We focus on owned assets in this paper, since real decisions such as investment expenditures capture spending on owned assets. We provide further discussions about the prevalence of operating leases in different industries in Internet Appendix Section IA6.1.

2.2 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, receivable, and book intangible, which correspond to the standard categories in financial statements. Each industry is a two-digit SIC code. Averaging by industry has two functions. First, the industry-level measures can reduce idiosyncratic noise at the individual case level. Second, they can be extended to firms in each industry more broadly, since asset specificity is to a large extent an industry attribute driven by the nature of production activities (e.g., physical attributes of assets in different industries).

Table 1 lists the industry-level liquidation recovery rates and Table 2, Panel A, presents summary statistics. For PPE, the average liquidation recovery rate is 34% (i.e., the liquidation value of PPE is on average 34% of net book value). The value is higher in industries with more generic PPE, such as transportation services (69%). 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 show in Internet Appendix Section IA6.1), so a large part of their PPE consists of store decorations (e.g., leasehold improvements to customize commercial spaces) 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 3, we show that physical attributes of PPE (mobility, durability, and customization) can account for both the average level of PPE liquidation recovery rates and close to 40% of the variations across industries.

For inventory, the average industry-level liquidation recovery rate is 44%. The value is high for retailers such as auto dealers (88%) and apparel stores (75%), given the generic nature of their inventory. It is low for restaurants (15%), since their inventory primarily consists of perishable fresh food. Finally, Tables 1 and 2 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 4.2. They represent goodwill and other intangibles purchased from outside; many non-goodwill 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 and mining industries, recreation, apparel because of transferable licenses and usage rights (e.g., route rights and gate rights, excavation rights, 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 rather generic assets, the liquidation values could be lower than intuitions based on prototypical assets with large-scale secondary markets.[10] To ensure that the data does not contain systematic reporting biases, we perform extensive checks of its reliability in the next section. Inevitably, the data may

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

still contain noise. Nonetheless, in Section 4 and in Kermani and Ma (2021), we show that it is informative for explaining firms' investment decisions, organizational structures, and financial contracts; we also use the liquidation recovery rates predicted by assets' physical attributes and find similar results.

2.3 Data Informativeness and Generalizability

We perform a number of checks to examine the reliability of the data. In particular, one possible concern is that the liquidation values are based on estimates, which may introduce inaccuracies.[11] A related concern is that firms in Chapter 11 may have incentives to understate liquidation values in order 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. Finally, one can be concerned that firms in Chapter 11 differ from the typical non-financial firm, because Chapter 11 may occur when the firm, its industry, or the economy experiences unfavorable conditions.[12] In terms of economic conditions, about 12% of our data comes from NBER recessions and 33% from industry recessions (i.e., industry revenue growth in the bottom quartile), so the data does not overwhelmingly represent severe downturns.

The checks in this section verify that our data is consistent with market-based outcomes, including auction results when such data is available. The checks also show that although detailed reporting is mainly available for Chapter 11 firms, our data is consistent with additional information collected from non-financial firms more generally. Furthermore, as we document in Section 3, the degree of asset specificity is shaped by the physical attributes of assets used in a given industry (measured among all firms in an industry). While macro and industry conditions can affect liquidation values, they do not easily erase differences across industries or lead to drastically different overall liquidation recovery rates. Lastly, Section 4 also demonstrates that the data performs well for explaining the outcomes of firms in general.

First, we cross-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), the liquidation recovery rate on machinery and equipment is 32%, which is similar. In addition, we obtain information on auctions

[11] Because the liquidation recovery rates are normalized by the net book value of assets, we also verify that the depreciation rates firms use for book assets are reasonable. In Internet Appendix Section IA6.2, we show that the depreciation rates that firms use are similar to those used by the BEA.

[12] In addition, a possible concern is that Chapter 11 firms may strategically sell off some of their assets. Maksimovic and Phillips (2001) find that firms sell high quality assets, whereas Franks et al. (2021) suggest that firms sell low quality assets. Although it is difficult to determine what happens in a particular case, later we show that the liquidation recovery rates in our sample align closely with asset attributes measured based on *all firms in an industry* using BEA data.

of construction equipment from EquipmentWatch (Murfin and Pratt, 2019) as well as the vintage and original price. This allows us to compute the replacement cost (book value net of depreciation) based on a depreciation rate estimation following Ramey and Shapiro (2001).[13] We find that the average liquidation recovery rate is 55% in this auction data, which is the same as the value for construction equipment implied by our data.[14]

Second, in Kermani and Ma (2021), 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.[15] As a result, we cannot use this data for our main analyses where we need to measure the specificity of a given type of assets (e.g., fixed assets). For firms in the same industry, we find 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 particular assets such as PPE and working capital, which reflect their assessments of the liquidation values of non-financial firms in general. 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 lenders use for inventory and receivable are also similar to the average liquidation recovery rates in our data, as we show in Kermani and Ma (2021).

Fourth, we also 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 lagged net PPE + capital expenditures − depreciation − current net PPE). This imputation is noisy because firms' PPE stock can change for many 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 0.45 (the mean is affected by extreme outliers due to imperfect imputation of the denominator). Alternatively,

[13]We use a quadratic depreciation function as in Ramey and Shapiro (2001): we start by regressing log auction values on equipment age and age squared, controlling for equipment model fixed effect, and then obtain net book value as original price times $\exp(-(\delta_1 \text{age} + \delta_2 \text{age}^2))$ where δ_1 and δ_2 come from the depreciation rate estimation.

[14]In particular, our liquidation recovery rate data is at the industry level, so we combine it with the BEA's fixed asset table that documents the composition of fixed assets in each industry (e.g., the fraction of construction equipment as well as other types of fixed assets). This allows us to calculate the implied liquidation recovery rate for construction equipment.

[15]In addition, in Chapter 7 cases the trustee may also abandon assets that have little value, or return assets that have negative equity (i.e., assets with liquidation value less than the amount of liabilities against them) to lenders to foreclose. The value of these assets is not recorded in the total liquidation proceeds realized by the trustee, which can create complications. We follow Bris, Welch, and Zhu (2006) to compute lower-bound and upper-bound estimates of total liquidation values, by assuming either none or all assets pledged to creditors are abandoned and foreclosed.

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 0.32. Overall, these estimates implied by PPE sales among Compustat firms are largely in line with the average liquidation recovery rates in our data. Since 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.

Fifth, we investigate whether the liquidation recovery rates or sale recovery rates of PPE are affected by firm characteristics within an industry, which we analyze in Internet Appendix Table IA3. We find that PPE liquidation recovery rates have a positive association with firms' operating earnings (EBITDA). In terms of the economic magnitude, if profitability (EBITDA normalized by book assets) changes by ten percentage points, PPE liquidation recovery rates would change by around one percentage point. This sensitivity is relatively small, given that the inter-quartile range of profitability among Compustat firms is around 25 percentage points (between -0.08 to 0.16).[16]

Finally, in Section 3, we demonstrate 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. Accordingly, our data reflects key features of assets shared by firms in an industry. Macroeconomic and industry conditions can affect liquidation recovery rates, but they do not easily change the overall picture driven by assets' physical attributes. As Ramey and Shapiro (2001) articulate, many production assets in practice are customized or immobile, so they often have limited value for alternative users or need substantial modifications to be useful. In Section 4, we show that the liquidation recovery rates in our data can account for firm outcomes both in the US (e.g., Compustat) and around the world.

2.4 Firm-Level Liquidation Values

We also calculate the estimated firm-level liquidation value for firms in Compustat:

$$Liq_{i,t} = \sum_{j} \lambda_{i,j} K_{i,j,t}, \tag{1}$$

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

[16]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* rather than the quality of the current business (e.g., the real estate of a bookstore making losses may have high liquidation values, while the customized equipment of a pharmaceutical company making profits may have little liquidation values).

(based on the firm's industry), and $K_{i,j,t}$ is the book value of asset j for firm i at time t. The 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. As discussed above, there is substantial consistency within an industry, and the industry-level liquidation recovery rates are informative.

Table 2, 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 (1). 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 inter-quartile range is about 30% to 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 post-emergence 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 50% (inter-quartile range 32% to 75%). 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 34% (inter-quartile range 20% to 53%). The data suggests 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, 2021).

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.

3 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 3.1, we demonstrate the importance of physical attributes of the assets used in different industries. In Section 3.2, we examine the impact of time-varying macroeconomic and industry conditions. We focus on fixed assets below and study the determinants of the specificity of inventory and other assets in Internet Appendix Sections IA4 and IA5.

3.1 Physical Attributes

We analyze three physical attributes that 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 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). The third attribute is the degree of customization: some assets are standardized or readily usable by other firms, while other assets are customized for a particular user. These three attributes can be measured consistently for all types of assets across industries. All of them affect the distribution of the asset's productivity for alternative users, which can be illustrated using the modeling framework in Gavazza (2011) and Bernstein, Colonnelli, and Iverson (2019). If an asset is less mobile, less durable, or more customized, there will be fewer alternative users with high valuation and the liquidation recovery rate will be lower.

3.1.1 Measurement of Physical Attributes

To study the physical attributes of PPE in each industry, a helpful starting point is the BEA's fixed asset table, which records the stock of 71 types of equipment and structures (listed in Internet Appendix Table IA7) across 58 BEA industries. We denote the fixed asset stock as K_{ij}, where i is a BEA industry and j is one type of fixed asset. We analyze the physical attributes of each type of fixed asset (j), and then assess the overall characteristics of PPE in an industry (i) using the fixed asset composition (the share of K_{ij} in $K_i = \sum_j K_{ij}$).[17] We explain the details of the measurement below.

Mobility. We measure the mobility m_j for each type of PPE using the ratio of its transportation costs (from producers to users) to its production costs. For each of the 71 fixed assets, we obtain this ratio using the BEA's input-output table (we link assets in the fixed asset table and the input-output table using the BEA's PEQ bridge). The transportation cost data is generally available for equipment, but may not be available for structures such

[17] The stock of fixed assets in each industry in the BEA data is based on ownership, i.e., 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 2.1.

as buildings, in which case we use a ratio of one (i.e., buildings are completely immobile). Among non-structures, assets with the lowest transportation costs (highest mobility) include computers, ships, and aircraft. Assets with the highest transportation costs include nuclear fuel and furniture.

We calculate the industry-level PPE mobility M_i by taking the weighted average across the 71 types of assets, where the weight is the share of the asset in the industry's total fixed asset stock based on the BEA fixed asset table: $M_i = \sum_j m_j \times (K_{ij}/K_i)$. Accordingly, the industry-level mobility measure is the ratio of total transportation costs of all PPE to the total production costs of all PPE. We match BEA industries with two-digit SICs (the industry codes in our liquidation value data). Table IA8 in the Internet Appendix lists the 58 industries in the BEA fixed asset table and the corresponding two-digit SICs. Industries with the highest overall PPE mobility (lowest transportation costs) include water transportation and business services. Industries with the lowest overall PPE mobility (highest transportation costs) include amusement parks and personal services.

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. Industries with the highest overall PPE durability (lowest overall PPE depreciation rate) include utilities, mining, and primary metal manufacturing. Industries with the lowest overall PPE durability (highest overall PPE depreciation rate) include business services, motion pictures, and construction.

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. The idea is that customized assets tend to require more design. For each of the 71 fixed assets, we calculate this share using the BEA's input-output table (i.e., we look at what it takes to produce each type of PPE).[18] Specifically, we find the sector that produces each type of PPE in the input-output table similar to Vom Lehn and Winberry (2021) and record how much it spends on design. A related proxy for the degree of standardization/customization is the share of cost of goods sold (which includes the cost of raw materials but not the cost of design, R&D, etc.) in the total operating cost of the sector that produces the asset, which leads to similar results. Nonetheless, an imperfection is that some standardized assets may also be design intensive (e.g., aircraft), which can work against us. Input assets with the highest customization include communication equipment and medical equipment. Input assets with the lowest customization include commercial structures and mobile structures.

[18] 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.

We calculate the industry-level PPE customization C_i by taking the weighted average across the 71 types of assets: $C_i = \sum_j c_j \times (K_{ij}/K_i)$. 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 SICs. Industries with the highest overall degree of PPE customization include manufacturing and business services. Industries with the lowest overall degree of PPE customization include education and hotels.

Other Attributes. Several previous studies use the overall market size of an asset to measure its market thickness and 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 (2008) studies railroads in the 19th century and measures redeployability using the size of railroads with a certain gauge. However, it can be more difficult to come up with such a measure across different industries. In particular, a given type of aircraft or railroad equipment is reasonably well defined. For the 71 types of assets in the BEA fixed asset table, on the other hand, the market size can change depending on the granularity of each asset category. For instance, in this data the asset type with the largest stock is manufacturing structures; if the BEA alternatively breaks down manufacturing structures by industry, then the market size for each type of manufacturing structure would be smaller. Additionally, Bernstein, Colonnelli, and Iverson (2019) measure the redeployability of plants using the probability that a plant in one industry is subsequently used in another industry. Tracking the flow of all types of assets across industries can be challenging in our setting, and inference based on the BEA fixed asset table is again affected by the granularity of asset categories (asset categories with a broader definition such as manufacturing structures are used by more industries than those with a narrower definition such as aircraft).[19]

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). Since the commodities in Rauch (1999) map more closely into inventory than fixed assets, we provide further discussions about Rauch (1999) when we investigate the determinants of inventory liquidation recovery rates in Internet Appendix Section IA4. In particular, the market structure of commodity trading 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

[19] Kim and Kung (2017) construct a proxy for asset redeployability using the number of industries that purchase a certain type of asset according to the BEA capital flow table. This measure could be affected by the granularity of the BEA's asset categories (e.g., the capital flow table has a type of asset named "Special tools, dies, jigs, and fixtures" which is), and this measure does not seem to explain the PPE liquidation recovery rates in our data. In addition, some of the most mobile, durable, and standardized assets are used in only a few industries (e.g., ships and railroad equipment), whereas many assets used in a large number of industries can be costly to move, non-durable, or customized (e.g., computers and optical lenses).

on organized exchanges.[20]

In sum, we focus on three measures of physical attributes (mobility, durability, and customization) that can be consistently constructed across industries for all types of assets. Although these three 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 table and input-output table to construct the physical attribute measures. Since the BEA only produces input-output accounts every five years, the year 1997 provides comprehensive information and predates our liquidation recovery rate data. Internet Appendix Table IA9 shows the industry-level summary statistics for two-digit SIC industries.

3.1.2 Explanatory Power of Physical Attributes

In Table 3, 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 substantial explanatory power for PPE liquidation recovery rates. Industries where PPE has high transportation costs, high depreciation rates, or high degrees of customization have low PPE liquidation values. The effects are statistically and economically significant. A one standard deviation change in mobility (transportation cost), durability (depreciation rate), and customization (design cost) is associated with changes in PPE liquidation recovery rate of 1.15, 0.29, and 0.69 standard deviations respectively, based on column (1). Moreover, the constant is around one, indicating that when physical frictions for reallocation are absent—namely if PPE is costless to transport, fully durable, and not customized—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. Finally, the R^2 of 30% to 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. Overall, our results show that specificity in location, time span, and usage (due to low mobility, low durability, and high customization, respectively) are key contributors to the low liquidation values of non-financial firms' assets.

In Table 3, Panel A, columns (2) and (4), we also include measures of industry size (an industry's sales share in Compustat and value-added share in BEA data), following the

[20]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 due to not only particular trading relationships but also other reasons such as transportation costs, perishability, and special design (e.g., aquariums, fresh food, eyeglasses). Second, the asset specificity we measure focuses on non-human assets, but relationship specificity can also arise from human capital (Williamson, 1996).

observations of Gavazza (2011) that larger and thicker markets may face fewer frictions for asset resales. We find a positive but relatively weak impact of industry size in our data.

In sum, 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.

3.2 Macroeconomic and Industry Conditions

Next we examine how macro and industry conditions affect PPE liquidation values. A number of studies point to the time-varying capacity of alternative users of assets, driven by business cycles (Kiyotaki and Moore, 1997; Lanteri, 2018) or industry conditions (Shleifer and Vishny, 1992; Benmelech and Bergman, 2011). For macro conditions, we use real GDP growth in the past twelve months. For industry conditions, we study industry leverage following the spirit of Shleifer and Vishny (1992): if alternative users primarily come from the same industry, then liquidation values are likely to fall when firms in the industry are constrained due to high indebtedness. We also find similar results using other proxies of industry conditions, such as industry sales growth.

For this analysis, it is useful to understand the scope of alternative users for a given type of assets: are they economy-wide or industry-wide, or difficult to find in any case? Accordingly, we identify firm-specific assets that could be customized to a particular firm (if the customization measure is in the top tercile). Examples of assets that are not firm-specific include vehicles and commercial real estate. Examples of assets that are firm-specific include communication equipment, medical instruments, and industrial machinery. After assigning each of the 71 assets in the BEA fixed asset table into a category, we calculate the (value-weighted) share of an industry's assets that belong to each category.

In Table 3, Panel B, we use the PPE liquidation recovery rate of each individual firm to examine the impact of time-varying macro conditions and industry conditions. We use GDP growth rate and industry leverage at the time of the liquidation analysis. We control for industry fixed effects to study how the liquidation recovery rate within an industry changes over time with economic conditions. For macroeconomic conditions, column (1) shows a weak positive correlation between GDP growth and PPE liquidation recovery rates on average. Nonetheless, column (2) shows the positive relationship is stronger when a high fraction of PPE is not firm-specific. If no PPE is firm-specific, then a one percentage point increase in GDP growth is associated with a roughly 3.2 percentage point increase in PPE liquidation recovery rates. For industry conditions, columns (3) and (4) show that PPE liquidation recovery rates are lower when industry leverage is higher; this relationship is also especially strong when most PPE is not firm-specific. On average, a one percentage point increase in industry leverage is associated with a 0.33 percentage point decrease in PPE liquidation recovery rates; the magnitude is close to zero if all PPE is firm-specific, and close to 0.6 if none is firm-specific. In other words, when assets are used across the economy or across an industry, the liquidation recovery rates are more sensitive to macro and industry conditions. When assets are customized to a particular firm and there are few alternative users to begin with, macro and industry conditions appear to matter less.

We also analyze the impact of macro and industry conditions in a detailed dataset of heavy equipment auctions between 1994 and 2013 studied by Murfin and Pratt (2019). The data is most comprehensive for construction equipment, which is one example of assets that are not highly firm-specific. For over 80,000 construction equipment in these auctions, we can find the original price of the equipment to calculate the auction recovery rate (i.e., auction value normalized by net book value). For other equipment (including construction equipment as well as tractors, trucks, etc.), we can perform hedonic regressions of log auction values on macroeconomic conditions. We find that a one percentage increase in real GDP growth is associated with a roughly two percentage point increase in the auction recovery rate and the log auction value, as shown in Panel A of Table IA4. This sensitivity is similar to what we find for non-firm-specific fixed assets in the second column of Table 3, Panel B, and the statistical power is much stronger in this large sample of equipment auctions. In addition, we also combine auctions of construction equipment with conditions in construction industries (two-digit SICs 15 to 17). Panel B of Table IA4 shows that when industry leverage (measured using Compustat firms) increases by one percentage point, auction recovery rates decrease by around 0.5 percentage points. This sensitivity to industry conditions is again similar to what we find for non-firm-specific fixed assets in the final column of Table 3, Panel B.[21]

Based on these estimates, we can also evaluate how much macro or industry conditions need to change to bring PPE liquidation recovery rates from the highest industries (e.g., transportation services at around 69%) to the median (e.g., a typical manufacturing industry at around 35%). Even if all of an industry's PPE is not firm-specific, to induce a 34 percentage point change, real GDP growth needs to change by 10.5 percentage points ($0.34/3.24 = 0.105$) and industry leverage needs to change by about 59 percentage points ($0.34/0.58 = 0.59$). Both are over three standard deviations of these variables, which suggests that it takes considerable fluctuations in economic conditions to have such large effects on liquidation recovery rates. Figure IA1 visualizes the relationship between PPE liquidation recovery rates and industry leverage for different types of industries. The solid red and hollow blue dots

[21] Using the data on used aircraft prices in Lanteri (2018), we also find a similar sensitivity of log prices to GDP growth and airline industry leverage. Since we do not know the original price in this data, it is difficult to analyze the sale recovery rate.

represent industries with more general and more specific PPE respectively (i.e., industry-average PPE liquidation recovery rate in the top and bottom tercile). This plot shows that liquidation recovery rates are more sensitive to industry conditions when PPE is more general, as discussed above. In addition, the differences across industries in asset specificity are substantial and not easily offset by time-varying industry conditions. Overall, our results provide evidence for cyclical variations in liquidation values; nonetheless, these fluctuations do not lead to drastic changes in the overall picture of high asset specificity.

4 Implications

In this section we examine the leading implications of asset specificity. In Section 4.1, we study the consequences of investment irreversibility. We show that disinvestment is less common when asset specificity is higher. Moreover, we provide direct evidence that uncertainty negatively affects investment when assets are specific, whereas the impact is absent when assets are generic. Higher asset specificity is also associated with more productivity dispersion. In Section 4.2, we illuminate the economic impact of intangible capital. We demonstrate that, in contrast to conventional wisdom, intangibles have not had a first-order impact on firms' liquidation values. Instead, their special feature could be scalability given their non-physical nature. In Section 4.3, we investigate the boundaries of firms. We document that firms vertically integrate more in countries with weaker legal institutions when asset specificity is high.

It is also natural to ask how asset specificity affects debt contracts and borrowing capacity, which we study in a companion paper (Kermani and Ma, 2021). We show that many firms have debt and total liabilities exceeding liquidation values. For total borrowing, liquidation values do not play a role among large firms and firms with positive earnings; they do have a significant positive relationship with total leverage among small firms and firms with negative earnings. Meanwhile, asset specificity affects debt composition: firms with higher liquidation values have more asset-based debt (lending on the basis of the liquidation value of discrete assets such as PPE and working capital), whereas firms with lower liquidation values have more cash flow-based debt (lending on the basis of the operating value of a company) and stronger creditor monitoring of their performance. These results align with observations in Lian and Ma (2021) about the importance of cash flow-based lending in the US: firms commonly borrow on the basis of their ability to generate cash flows as an operating business, and borrowing constraints are not necessarily determined by liquidation values.

The analyses in this section use all US non-financial firms in Compustat as well as firms around the world, combined with our asset specificity data based on industry. Accordingly, in addition to demonstrating the economic implications of asset specificity, the results also show that our data performs well for explaining the behavior of firms in general.

4.1 Investment Irreversibility

Investment irreversibility is a prominent theme in theories of investment (Bernanke, 1983; Pindyck, 1991; Caballero, 1999; Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2018). We provide direct evidence that investment irreversibility shapes investment activities among firms in the US and among different industries around the world. We also find that it affects productivity dispersion and price rigidity.

4.1.1 Investment Irreversibility and the Impact of Uncertainty

A. Prevalence of Disinvestment

We start by showing that disinvestment is indeed less common when asset specificity is higher and irreversibility is stronger. For firms in Compustat, we can measure the prevalence of fixed asset sales (disinvestment) using the variable "Sale of Property, Plant, and Equipment" (SPPE), which records proceeds from PPE sales. We measure both the frequency of PPE sales (the fraction of firm–years with SPPE>0) and the amount of sales (SPPE normalized by lagged net PPE). Figure 1 plots the average frequency of PPE sales per year in each two-digit SIC industry on the y-axis, and the industry-average PPE liquidation recovery rate on the x-axis (raw value in Panel A and predicted value based on physical attributes in Panel B). The data shows that PPE sales are more common in industries with lower PPE specificity (higher liquidation recovery rates). Figure IA2 shows similar patterns for the average PPE sale amount per year. Table 4 presents regressions using both the raw industry-level PPE liquidation recovery rates and those predicted by physical attributes (according to column (1) of Table 3, Panel A). In terms of magnitude, the frequency of PPE sales increases by 0.3 to 0.4 standard deviations for a one standard deviation increase in the industry-level PPE liquidation recovery rate, according to columns (1) and (3).[22] Taken together, we find that asset specificity is closely associated with disinvestment behavior.

B. Investment Response 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 5. We use the following firm-level annual regression to study how the

[22]For industries with high asset specificity, we find that capital reallocation is more likely to take the form of mergers and acquisitions, namely purchases of firms or segments as a whole (installed assets together with teams and organizational structures), instead of capital on a standalone basis. Nonetheless, although firms can potentially downsize through selling an entire division or segment, these changes are inevitably lumpier and more drastic, so firms with more specialized assets would face less flexibility in disinvestment overall.

investment response to uncertainty varies with the degree of asset specificity:

$$Y_{i,t+1} = \alpha_i + \eta_{j,t} + \beta\sigma_{i,t} + \phi\lambda_i \times \sigma_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}. \tag{2}$$

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) a la Gilchrist, Sim, and Zakrajšek (2014). The liquidation recovery rate is denoted by λ_i, which is matched to Compustat firms based on their industries. 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. The control variables $X_{i,t}$ include Q, book leverage, cash holdings, EBITDA, size (log book assets), and ratings 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 firm and time. We use a longer sample of 1980 to 2016 to allow for more variation in uncertainty over time.

In columns (1) to (2) of Table 5, Panel A, 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. This result matches closely with theoretical predictions and indicates that asset specificity is key to the negative impact of uncertainty on firm investment.

In columns (3) and (4) of Table 5, Panel A, we study inventory investment, which can also play an important role for economic fluctuations (see Ramey and West (1999) for a summary). We use inventory the liquidation recovery rate for λ and interact it with the uncertainty measure σ. We find that higher uncertainty is also associated with significant decreases 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 5, Panel B, we find that the impact of uncertainty on fixed asset investment is mainly affected by PPE liquidation recovery rates, while inventory liquidation recovery rates have a weaker impact. 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, there is a precise mapping between the specificity of one type of assets and its investment sensitivity to uncertainty. This clear correspondence also suggests that liquidation recovery rates primarily operate through mechanisms of investment irreversibility, instead of being proxies for a firm's overall financing constraints (e.g., borrowing capacity based on liquidation values). We also find similar results among large firms (which are less likely to be constrained) and small firms (which are more constrained, especially by liquidation values).

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.

C. Macroeconomic Volatility and Cross-Country Industrial Development

We then extend our analyses across countries and investigate how macroeconomic volatility in a country affects investment activities in industries with different levels of asset specificity (and correspondingly different degrees of investment irreversibility). In particular, we study a regression similar to Equation (2) above:

$$Y_{jkt} = \alpha_j + \beta\sigma_{kt} + \phi\lambda_j \times \sigma_{kt} + \gamma X_{jkt} + \epsilon_{jkt}, \tag{3}$$

where j denotes an industry, k denotes a country, and t denotes a year. The outcome variable Y_{jkt} is the gross fixed capital formation in industry j, country k, and year t, using data from the United Nations Industrial Development Organization (UNIDO) for International Standard Industrial Classification (ISIC) industries from 1996 to 2016. The data is available for manufacturing industries in about 100 countries. Macroeconomic volatility σ_{kt} is the volatility of per capita real GDP growth in country k over the past twenty years. Asset specificity λ_j denotes the liquidation recovery rate of PPE in industry j based on our data. Control variables X_{jkt} include log real GDP per capita, PPE share in total assets and external finance dependence in an industry following Rajan and Zingales (1995), as well as interactions of industry features with both GDP volatility and log GDP per capita. Like Rajan and Zingales (1995), we measure industry features on the right-hand side using US data (from Compustat) and rely on the assumption that these industry features (namely asset specificity, PPE share, and external finance dependence) are similar across countries.

Table 6 presents the results. Columns (1) to (3) use gross fixed capital formation in US dollars per capita. We find that higher macro volatility is associated with significantly lower fixed capital formation in industries with high specificity of fixed assets (low PPE liquidation recovery rates). This effect is absent, however, when PPE liquidation recovery rates are sufficiently high. Columns (4) to (6) use the share of gross fixed capital formation in each industry j in a country on the left-hand side. Analogously, countries with higher macro volatility have a lower share of investment in industries with high fixed asset specificity and a higher share of investment in industries with generic fixed assets. Columns (3) and (6) also include both industry-year and country-year fixed effects, and the interaction between macro volatility and asset specificity remains strong.

Overall, our findings echo the view that macroeconomic stability can affect economic development (Aizenman and Marion, 1993; Ramey and Ramey, 1995) and demonstrate that asset specificity modulates this impact. Investment in industries with generic assets is more robust to macro volatility, whereas industries with high asset specificity can be especially vulnerable to macro volatility.

4.1.2 Productivity Dispersion

In addition to shaping the impact of uncertainty shocks, investment irreversibility can also affect productivity dispersion (Eisfeldt and Rampini, 2006; Lanteri, 2018). Internet Appendix Figure IA3 shows that greater investment irreversibility leads to higher productivity dispersion in the model of Lanteri (2018). We also test this prediction in the data. Figure IA4 presents the relationship between the average annual dispersion in Q within each two-digit SIC industry (y-axis) and the average firm-level liquidation value of PPE and working capital (normalized by total book assets) in the industry (x-axis). 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. Table IA5 presents the corresponding results in regressions. The data shows that industries with lower liquidation values indeed have higher Q dispersion. Furthermore, this relationship holds for both large firms (total assets above median in Compustat each year) and small firms (total assets below median). This finding suggests the impact of liquidation values is not necessarily through borrowing constraints, since large firms' debt capacity is not primarily driven by liquidation values (Lian and Ma, 2021; Kermani and Ma, 2021). Instead, lower liquidation values can affect the productivity dispersion among both large and small firms due to higher investment irreversibility.

4.1.3 Price Rigidity

Finally, Woodford (2005) and Altig, Christiano, Eichenbaum, and Linde (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. 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 Table IA6, we collect information on industry-level price rigidity using the frequency of price change from Nakamura and Steinsson (2008) and Gorodnichenko and Weber (2016).[23] Given that in practice both PPE and inventory are relevant for production, we investigate each of them as well as the combined measure of the total liquidation value from PPE and working capital (normalized by book assets, as in Section 2.4). Figure IA5 visualizes the relationship between the industry-level frequency of price change (y-axis) and the industry-average firm liquidation value (x-axis). Overall, we find that prices indeed appear stickier in industries with higher asset specificity (lower liquidation values), and vice versa.

4.2 Economic Impact of Intangible Assets

Classic investment theories have focused on investment in fixed assets (or "tangible" capital). Recent research documents that a key development in the past few 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, 2020b), broadly defined as production assets without physical presence. Intangible assets include identifiable components such as computerized information (software, data, recordings), usage rights (licenses, excavation rights, route rights, domain names, 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 Perez-Orive, 2018; Falato et al., 2020), or in a similar vein increase the "sunkness" of firms' investment (Haskel and Westlake, 2018). 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 does not seem to have had a first-order impact on firms' liquidation values, contrary to conventional wisdom. We then document that intangible capital does seem to be associated with more scalability, possibly because the lack of physical presence makes intangibles more non-rival within a firm. In other words, the key difference between intangible assets and physical assets may not be the overall degree of asset specificity, but the degree of scalability.

[23] In the model of Altig et al. (2011) with Calvo pricing, having firm-specific capital affects the magnitude of price change. 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 change as in menu cost models.

4.2.1 Intangible Capital and Liquidation Values

We begin by analyzing the extent to which intangibles affect firms' asset specificity. In particular, we investigate the concern that rising intangibles may intensify frictions in firms' investment and financing by draining their liquidation values. As mentioned above, intangible capital includes different sets of non-physical assets, which can differ in their economic properties. Specifically, identifiable intangibles are generally transferable on a standalone basis (e.g., software, excavation rights, airlines' gate and route rights, patents), and our data provides information about their liquidation recovery rates. Other intangibles that are not separable from the firm (e.g., organizational capital) have no liquidation values.

We make three observations for understanding the impact of intangibles on firms' liquidation values. First, as shown previously, physical assets are already highly specific in many industries. For instance, given that the average industry-level liquidation recovery rate for PPE is 35%, even if PPE is replaced by intangible assets that have minimal liquidation recovery rates, the change in the total liquidation value may not be substantial.

Second, we show that the liquidation recovery rate of identifiable intangibles is not necessarily much lower than that of PPE (e.g., transferring intangibles do not incur transportation costs). Specifically, our data covers the liquidation recovery rate of "book intangibles," which are intangible assets purchased from external parties and therefore reported on balance sheets based on current US accounting rules (intangible assets developed internally, on the other hand, are not reported on balance sheets). These book intangibles represent identifiable intangibles (such as software, customer data, usage rights, patents, which can be acquired from external parties on a standalone basis) as well as goodwill (i.e., the difference between the total purchase price in a corporate acquisition and the net book value of all identifiable assets of the target company, which may come from the value of human and organizational capital, or from overpricing). Identifiable intangibles are separable and offer positive liquidation values, while goodwill has zero liquidation value by definition.

Figure 2 plots the average liquidation recovery rate of PPE versus book intangibles for Fama-French 12 industries (except finance). For each industry, the first bar represents the average PPE liquidation recovery rate, the second bar represents the average book intangible liquidation recovery rate, and the third bar represents the implied liquidation recovery rate of non-goodwill book intangibles (calculated as the average book intangible liquidation recovery rate divided by the industry-average share of non-goodwill intangibles in total book intangibles). 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 non-goodwill book intangibles is about 38%, and the inter-quartile range is 4% to 58%. Indeed, these values are comparable to PPE liquidation recovery rates on average, but with more dispersion.[24] In sum, identifiable intangibles can obtain liquidation values on their own, and are not necessarily more specific than tangible assets such as PPE.

Third, we find that the rise of intangibles so far has been especially pronounced in industries where physical assets are more specific in the first place. We use the 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 (specifically, they capitalize R&D spending to estimate knowledge capital and capitalize 30% of Selling, General, and Administration expenses to estimate organizational capital). Although these measures could be imperfect, the result we document holds using either approach.

Figure 3 plots the change in the industry-level share of intangible assets relative to the sum of fixed assets and intangibles from 1996 and 2016 (y-axis) against industry-level PPE liquidation recovery rates (x-axis). We use the BEA's measurement of intangibles in Panel A, and Peters and Taylor (2017)'s estimate in Panel B. Table 7 shows the results in regressions, using both the PPE liquidation recovery rates directly and the values predicted by the physical attributes of PPE. In all cases, industries with low PPE liquidation recovery rates have seen the most substantial increase in the prevalence of intangibles. In other words, the shift from physical assets to intangibles has been most pronounced where the liquidation values of fixed assets are already small and there is not much to "lose" further.

Finally, putting these observations together, Figure 4 shows the estimated liquidation value of all Compustat firms from 1996 to 2016, as a share of total book value in Panel A and as a share of total enterprise value (market value of equity plus book value of debt) in Panel B. Liquidation values include those from book intangibles, PPE, working capital, and cash. We see that the estimated liquidation value from PPE declines slightly over this period (by about 2% of book assets), which is 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., in the aggregate book intangibles increased from 9% of total assets to 26%). Indeed, the sum of liquidation values from PPE and book intangibles has stayed roughly constant (and always below 20% of both book value of assets and firm enterprise value).

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

Accordingly, based on our data, rising intangibles may not substantially deplete firms' liquidation values. Furthermore, in the US, firms' debt capacity is not necessarily tied to liquidation values, especially when firms have positive earnings (Kermani and Ma, 2021; Lian and Ma, 2021). Similarly, the results also suggest that investment irreversibility or sunkness may not increase significantly with rising intangibles. A set of identifiable intangibles such as licenses, data, and patents could be sold off and are partially reversible.

4.2.2 Intangible Capital and Scalability

If the first-order impact of intangible capital is not to deplete firms' liquidation values, 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, since intangibles are non-physical 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, Dorn, Katz, Patterson, and Van Reenen, 2020; Hsieh and Rossi-Hansberg, 2020; Lashkari, Bauer, and Boussard, 2020). In Table 8, we show that more intangibles are associated with higher employment shares of large firms and higher revenue concentration in an industry, whereas asset specificity does not have a similar effect.

In columns (1) to (3) of Table 8, we study the employment share of large firms (over 500 employees) for each four-digit NAICS industry from the Census Statistics of US Businesses (SUSB). In columns (4) to (6), we study the revenue share of the top 20 firms in each four-digit NAICS industry computed by the Census. We examine the relationship between the importance of large firms in an industry and knowledge capital, a form of intangible capital that is likely non-rival within a firm; it has also been measured by the BEA for various industries and by Peters and Taylor (2017) for firms in Compustat (both datasets capture capitalized R&D, and we use knowledge capital as a share of total fixed assets plus intangibles). Table 8 shows that a one percentage point increase in knowledge capital intensity is associated with a 0.3 to 0.5 percentage point higher employment share of large firms and a 0.2 to 0.3 percentage point higher revenue share of top 20 firms. On the other hand, higher asset specificity (e.g., lower PPE liquidation recovery rate) does not have such an effect. In other words, intangibles such as knowledge capital seem to have a distinct link with the dominance of large firms, which is not related to asset specificity.

Taken together, our data suggests that the key difference between intangible assets and physical assets may not arise from the degree of asset specificity. Instead, because intangible assets are defined by their lack of physical presence, they could be more scalable. These empirical findings shed further light on the essence of intangible assets, which remains an open question. Our analyses also complement recent work that examines another set of implications of intangible capital concerning the proper measurement of economic activities such as growth, investment, and productivity (Corrado, Hulten, and Sichel, 2005; Crouzet and Eberly, 2020b,a; Brynjolfsson, Rock, and Syverson, 2021).

4.3 Boundaries of the Firm

Our final application investigates the classic issue of the boundaries of the firm. A long-standing observation is that when a firm's production requires investment in assets with high specificity, it is more exposed to holdup problems by suppliers and customers, and transaction costs can be higher more generally (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, however, vertical integration can be more important. As noted in the survey 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 now allows us to test these insights across a broad set of industries and countries.

To measure the degree of vertical integration across countries and industries, we follow the methodology in prior work (Fan and Lang, 2000; Acemoglu, Johnson, and Mitton, 2009; Alfaro, Conconi, Fadinger, and Newman, 2016) and use data from ORBIS. 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. Specifically, we look at the industries of the firm's subsidiaries and measure the "upstreamness" of a subsidiary industry using its share in the inputs of the parent's industry, according to the BEA's input-output table. We measure the "downstreamness" of a subsidiary industry using the fraction of its inputs that comes from the parent's industry. 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 total vertical integration $S1$ ($S2$) is the sum of the upstreamness (downstreamness) of subsidiary industries that a parent firm has. We use the 2012 input-output table because its industry classifications are closest to the 2017 NAICS codes in ORBIS. This data covers over 100 countries, and we

[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 focuses 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 or not) as a proxy for the specificity of the product. In the data, this measure is not correlated with the specificity of PPE.

take the average scores for each country and industry (4-digit BEA code).[26] 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 country from the World Bank Governance Indicators as a proxy for contract enforcement; this variable has zero mean and unit variance.

Table 9 presents the results. Columns (1) and (4) show 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 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 US dollars) and the business sophistication index from the World Economic Forum Global Competitiveness Report. The business sophistication index captures the costs of running large integrated companies (whereas rule of law modulates the benefits from vertical integration); alternative proxies such as the quality of management schools show similar results. In columns (2) and (5), 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). The interaction between rule of law and asset specificity continues to hold. Finally, results are similar in columns (3) and (6), where we instrument the liquidation recovery rates of fixed assets using the physical attributes discussed in Section 3.1.

Taken together, our findings provide direct and systematic evidence across industries and countries that the combination of asset specificity and institutional environments shapes the degree of vertical integration.

5 Connections to Model Parameters

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

[26] Results are similar if we restrict to countries where ORBIS data covers more than a certain number of industries. We use firms that are active in 2012, as well as the rule of law index and other independent variables measured in 2012, to match the timing of the 2012 input-output table.

[27] Since our liquidation recovery rate data is based on US firms, this matching assumes that firms in the US have a limited degree of vertical integration, which is indeed the case based on the vertical integration scores. For 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).

5.1 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 (Bloom, 2009; Abel and Eberly, 1996). 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), implies larger losses from disinvesting fixed assets on a standalone basis. Our data also suggests that this loss can vary substantially across industries, which may lead to different patterns in industry dynamics.

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. However, if reallocation takes the form of mergers and acquisitions (which transfer not just fixed assets but also human and organizational capital), the loss may not be as substantial, but such adjustments are lumpy and difficult to implement if a firm simply wants to downsize its capital stock. Accordingly, high asset specificity inevitably limits firms' flexibility to disinvest and downsize.

5.2 Models of "Collateral Constraints"

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).[28] In other words, firms' borrowing b is restricted by the liquidation value of the capital stock K, $b \leq \lambda K$, where λ is then the liquidation recovery rate. Although this form of borrowing constraint may not be first-order among major non-financial firms in the US (Lian and Ma, 2021), it is more prevalent among small firms and firms with negative earnings, and models may find liquidation value data relevant in these settings.

Models of 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. (2019) imply that firms can only borrow around 15% to 20%, which are close to the PPE liquidation recovery rate in our data. The main reason for the different parameters seems

[28]We use "collateral constraints" in quotes 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 US 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.

to be that the former set of papers match the total leverage of firms, while Catherine et al. (2019) 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 debt capacity may not necessarily reflect the tightness of the traditional collateral constraints. On the other hand, 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., 2019). The findings in our data are also similar to the results in Evans and Jovanovic (1989), where the model estimates suggest that entrepreneurs can borrow around 31% to 42% of their capital stock.

Overall, the data suggests that if firms only borrow against the piecemeal liquidation value of assets such as PPE, then debt capacity is rather limited. This type of borrowing constraint is typically bounded by the liquidation value, which is 35% for PPE in the average industry based on our data. According to lenders, common debt limits against industrial PPE are also 20% to 30% of the book value. Correspondingly, for models where firms can only borrow against the liquidation value of fixed assets, this low level of debt capacity would apply to most industries.

6 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 dataset on assets' liquidation values, which covers all major categories of assets in different 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 document that physical attributes of assets used in different industries have strong explanatory power for both the level and the cross-industry variations of asset specificity. In addition, macro and industry conditions affect liquidation values the most when assets are not customized to a given firm, but they do not seem to change the overall high degree of asset specificity or offset the substantial cross-industry differences.

The new data also illuminates 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 present direct empirical evidence that asset specificity is essential to the impact of both firm-level uncertainty and macroeconomic volatility, and the negative effect of uncertainty is absent if assets are generic.

Moreover, we provide insights into the economics of intangible capital. Our results suggest that the first-order impact of intangible assets may not be to reduce firms' liquidation values. Instead, the distinct feature of intangibles could be their scalability, facilitated by their lack of physical presence. Finally, we demonstrate that the combination of asset specificity and contractual environments shifts the boundaries of firms across countries and industries. Taken together, we hope the data and analyses inform our understanding of the nature of firms' assets and its wide-ranging impact.

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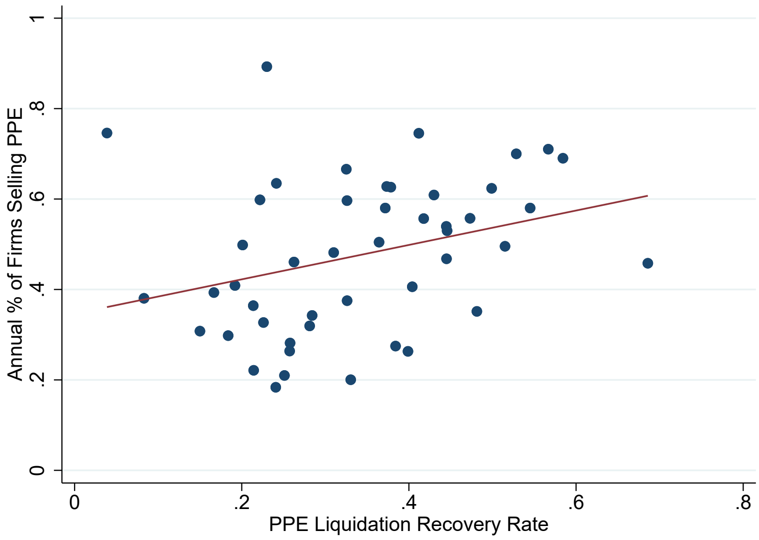
Main Figures and Tables

Figure 1: 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 non-zero 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 3, Panel A) in Panel B. The sample period is 1996 to 2016. Each industry is a two-digit SIC.

Panel A. PPE Liquidation Recovery Rate and PPE Sale Frequency



Panel B. PPE Liquidation Recovery Rate based on Physical Attributes and PPE Sale Frequency

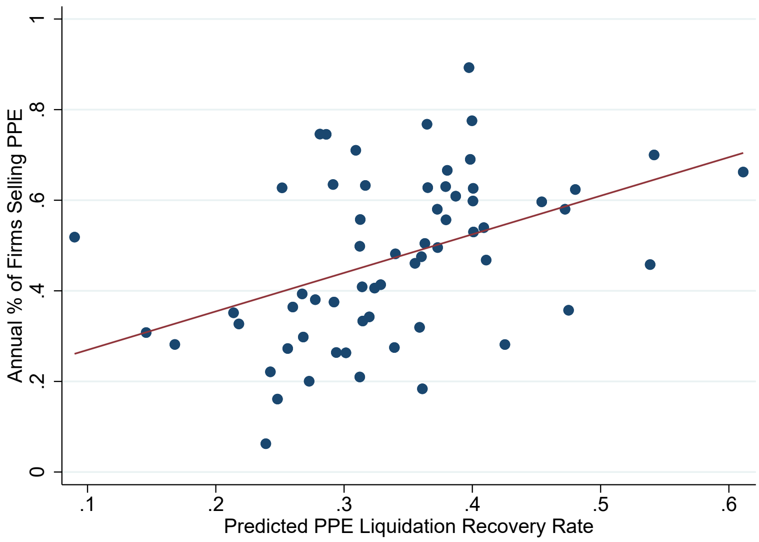


Figure 2: Industry-Average Liquidation Recovery Rate: PPE versus Book Intangibles

This figure shows the liquidation recovery rate of PPE versus book intangibles in Fama-French 12 industries (except financials). For each industry, the first bar shows the mean liquidation recovery rate of PPE. The second bar shows the mean liquidation recovery rate of book intangibles. The third bar shows the estimated liquidation recovery rate of book intangibles excluding goodwill, calculated as the mean book intangible liquidation recovery rate divided by the share of non-goodwill assets in book intangibles in the industry. In other words, goodwill has no liquidation value, so all of the liquidation value of book intangibles comes from non-goodwill assets.

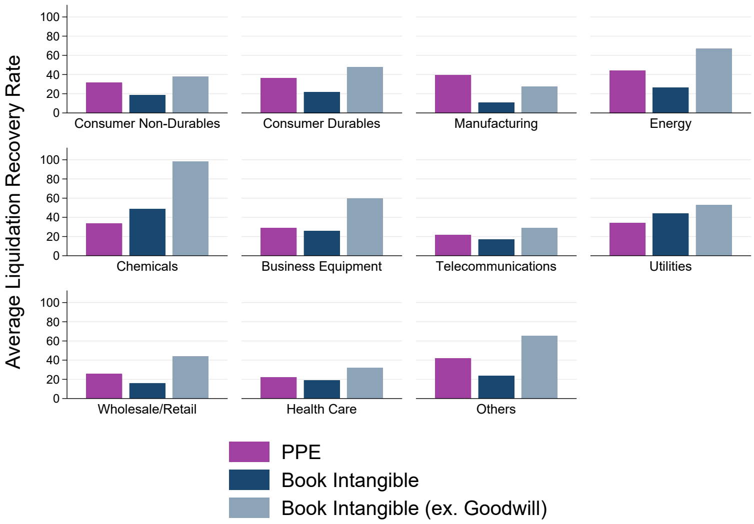
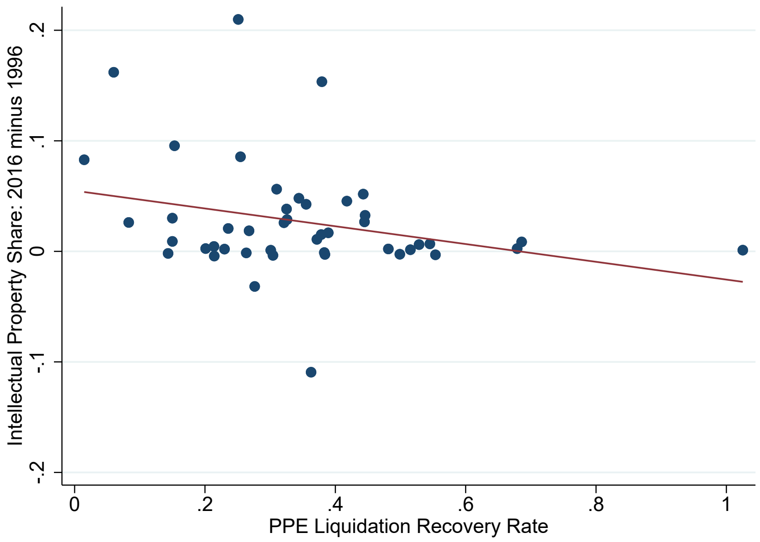


Figure 3: Specificity of Fixed Assets and Rising Intangibles

This figure shows binscatter plots of the rise of intangibles by the level of the PPE liquidation recovery rate. Panel A uses BEA's 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 1996 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 1996 to 2016, and the x-axis is the PPE liquidation recovery rate of the firm based on its industry.

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



Panel B. Firm-Level Intangible Assets (Compustat)

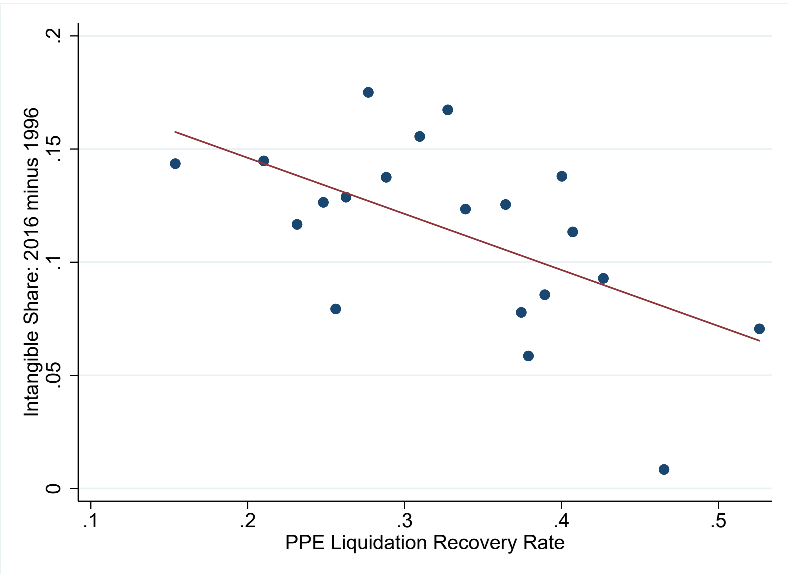
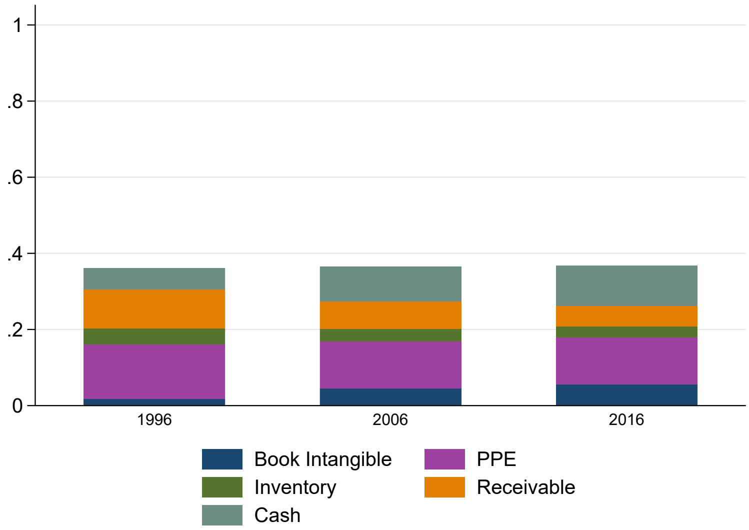


Figure 4: Liquidation Value over Time (Compustat Aggregate)

This figure shows the estimated total liquidation value from PPE, working capital, book intangibles, and cash among all Compustat firms from 1996 to 2016. Panel A shows total liquidation value as a share of total book assets. Panel B shows total liquidation value as a share of total enterprise value (debt plus market value of equity).

Panel A. Total Liquidation Value/Total Book Assets



Panel B. Total Liquidation Value/Total Enterprise Value

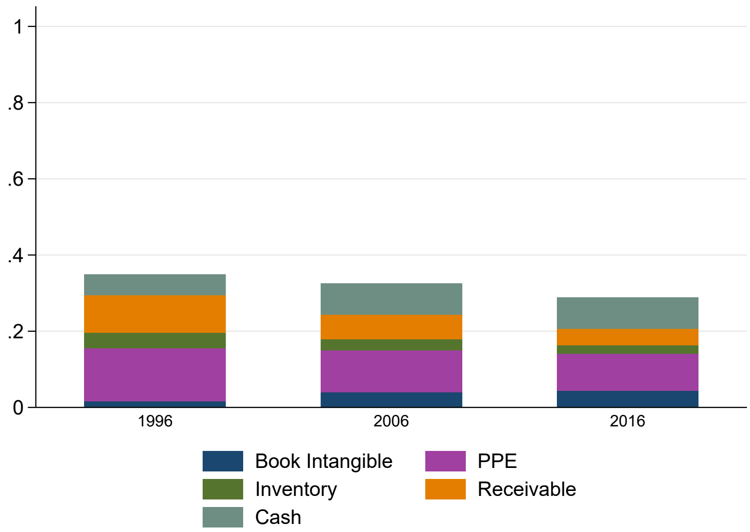


Table 1: Liquidation Recovery Rate by Industry and Asset Type

This table presents the average liquidation recovery rate (liquidation value/book value) for each asset category in each two-digit SIC. The column "Intan (ex. goodwill)" is the liquidation recovery rate of book intangibles excluding goodwill, calculated using the liquidation recovery rate of book intangibles divided by the industry-average share of non-goodwill in total book intangibles (since goodwill has no liquidation value).

SIC2	PPE	Inventory	Receivable	Intangible	Intan (ex. goodwill)
10 Metal Mining	0.24	0.44	0.44	0.02	0.03
12 Coal Mining	0.22	0.56	0.79	0.36	0.62
13 Oil/Gas Extraction	0.47	0.41	0.73	0.23	0.63
14 Quarrying-Nonmetals	0.45	0.50	0.73	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	0.00	0.00
20 Food Products	0.37	0.46	0.74	0.09	0.19
22 Textile Products	0.43	0.52	0.64	0.25	0.71
23 Apparel Products	0.19	0.47	0.66	1.09	2.15
24 Wood Products	0.58	0.32	0.79	0.04	0.20
25 Furniture and Fixtures	0.33	0.35	0.71	0.06	0.18
26 Paper Products	0.33	0.59	0.64	0.05	0.14
27 Printing and Publishing	0.31	0.34	0.63	0.14	0.35
28 Chemical Products	0.25	0.50	0.62	0.38	0.59
30 Rubber and Plastics Products	0.45	0.48	0.63	0.10	0.25
32 Stone, Clay, Glass, and Concrete	0.42	0.43	0.71	0.00	0.00
33 Primary Metal	0.44	0.62	0.66	0.24	0.60
34 Fabricated Metal Products	0.38	0.46	0.69	0.02	0.04
35 Machinery	0.40	0.45	0.48	0.05	0.13
36 Electronic Equipment	0.28	0.29	0.62	0.50	0.99
37 Transportation Equipment	0.36	0.59	0.61	0.21	0.56
38 Analytical Instruments	0.40	0.37	0.89	0.32	0.63
39 Misc. Manufacturing	0.33	0.67	0.67	0.28	0.58
41 Local Transit	0.53	0.32	0.74	0.00	0.00
42 Motor Freight	0.23	0.34	0.65	0.02	0.08
44 Water Transportation	0.55	0.57	0.55	.	.
45 Transportation by Air	0.50	0.47	0.39	1.36	2.49
47 Transportation Services	0.69	0.58	0.50	0.00	0.00
48 Communications	0.21	0.26	0.56	0.17	0.29
49 Electric and Gas	0.38	0.36	0.90	0.34	0.44
50 Wholesale Durables	0.26	0.41	0.72	0.05	0.17
51 Wholesale Non-Durables	0.52	0.46	0.56	0.21	0.55
52 Building Materials Dealers	0.57	0.29	0.21	0.00	0.00
53 General Merchandise Stores	0.24	0.61	0.54	.	.
54 Grocery Stores	0.41	0.75	0.58	0.10	0.30
55 Automotive Dealers	0.04	0.88	0.55	0.00	0.01
56 Apparel Stores	0.18	0.75	0.70	0.32	0.68
57 Furniture Stores	0.17	0.58	0.78	.	.
58 Restaurants	0.20	0.15	0.57	0.19	0.47
59 Misc. Retail	0.23	0.44	0.56	0.01	0.04
70 Lodging	0.48	0.48	0.68	0.10	0.19
72 Personal Services	0.08	0.15	0.54	0.01	0.04
73 Business Services	0.33	0.43	0.63	0.06	0.17
78 Motion Pictures	0.26	0.37	0.52	0.01	0.02
79 Amusement and Recreation	0.21	0.31	0.63	0.42	0.88
80 Health Services	0.26	0.38	0.49	0.06	0.21
82 Educational Services	0.15	0.15	0.37	0.08	0.21

Table 2: Summary Statistics

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. Mean, mediam, standard deviation, and quartiles are presented. The liquidation values for Compustat firms are estimated using Equation (1) in Section 2.4.

Panel A. Industry-Level Liquidation Recovery Rates

	mean	p50	sd	p25	p75
PPE	33.97	32.61	13.85	23.00	44.48
Inventory	44.26	43.92	15.66	33.70	56.30
Receivable	61.60	63.03	13.64	55.07	70.76
Book intangible	18.10	8.38	26.97	1.52	24.75
Book intangible (ex. goodwill)	38.15	20.07	50.73	3.88	58.30

Panel B. Firm-Level Total Liquidation Value

	mean	p50	sd	p25	p75
Firms in Chapter 11 Liquidation Analysis Sample					
Total liquidation value/book assets	0.43	0.42	0.23	0.26	0.58
Total liquidation value/going-concern value	0.58	0.50	0.41	0.32	0.75
Compustat Firms (2000—2016)					
Total liquidation value/book assets	0.46	0.44	0.19	0.34	0.57
Total liquidation value/going-concern value	0.41	0.34	5.78	0.21	0.53

Table 3: Determinants of PPE Liquidation Recovery Rates

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. Depreciation rate measures durability. Design cost share (in total production cost of PPE) measures customization. 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 SICs; 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. Past 12-month GDP growth and industry leverage are measured as of the quarter of the liquidation analysis. In columns (2) and (4), we interact GDP growth and industry leverage with the fraction of fixed assets in the industry that are not firm-specific (the top tercile of the 71 types of fixed assets in the BEA fixed asset table by design costs are designated as firm-specific). 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. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A. Physical Attributes and Industry-Average Liquidation Recovery Rates

	Industry-Level PPE Liquidation Recovery Rate			
	Industry Classification			
	Two-Digit SICs		BEA Industries	
Transportation cost	-0.77***	-0.79***	-0.58***	-0.67***
	(0.17)	(0.18)	(0.21)	(0.22)
Depreciation rate	-0.78***	-0.79***	-1.32**	-1.35**
	(0.26)	(0.26)	(0.51)	(0.51)
Design cost share	-22.25***	-23.30***	-19.88**	-21.76**
	(7.38)	(7.71)	(9.31)	(9.30)
Industry size (sales share)		0.39		
		(0.59)		
Industry size (value-added share)				1.46
				(1.13)
Constant	1.20***	1.22***	1.16***	1.21***
	(0.21)	(0.22)	(0.27)	(0.27)
Obs	47	47	45	45
R^2	0.36	0.36	0.28	0.32

Panel B. Impact of Macroeconomic and Industry Conditions

	Case-Level PPE Liquidation Recovery Rate			
	(1)	(2)	(3)	(4)
GDP gr	0.46	-2.90		
	(0.70)	(1.95)		
GDP gr × fraction PPE non-firm specific		6.14		
		(3.95)		
Industry lev			-0.33***	-0.03
			(0.06)	(0.13)
Industry lev × fraction PPE non-firm specific				-0.55***
				(0.12)
Fixed effect	Industry			
Controls	N	Y	N	Y
Obs	349	349	349	349
R^2	0.002	0.008	0.025	0.028

Table 4: PPE Liquidation Recovery Rates and Prevalence of PPE Sales

This table shows industry-level regressions that study the relationship between PPE liquidation recovery rates and the prevalence of disinvestment in the form of PPE sales. The outcome variable is the average fraction of firms with non-zero PPE sales every year in columns (1) and (2), and average PPE sale proceeds (Compustat SPPE) normalized by lagged net PPE (Compustat PPENT) in columns (3) and (4). We use the raw industry-level PPE liquidation recovery rates when "IV" is labeled "No," and the PPE liquidation recovery rates predicted by physical attributes (mobility, durability, customization shown in column (1) of Table 3, Panel A) when "IV" is labeled "Yes." The sample period is 1996 to 2016. Each industry is a two-digit SIC. Robust standard errors are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

	Frequency of PPE Sales		PPE Sold/Net Book PPE	
	(1)	(2)	(3)	(4)
PPE liquidation recovery rate	0.330**	0.923***	0.061*	0.064**
	(0.133)	(0.274)	(0.033)	(0.025)
Constant	0.362***	0.153	-0.001	-0.002
	(0.060)	(0.096)	(0.011)	(0.008)
IV	No	Yes	No	Yes
Obs	48	48	48	48
R^2	0.10		0.30	

Table 5: Asset Specificity and Investment Response to Uncertainty

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) to (2), $Y_{i,t+1}$ is 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) to (4), $Y_{i,t+1}$ is inventory investment (changes in total inventory, normalized by lagged inventory), and λ_i is the inventory liquidation recovery rate based on firm i's industry. $\sigma_{i,t}$ is firm-level annual stock return volatility in columns (1) and (3), and annual abnormal volatility (based on the Fama-French three-factor model) in columns (2) and (4). In Panel B, the variables are the same. The controls $X_{i,t}$ include Q (market value of assets/book value of assets), book leverage, cash holdings, EBITDA (normalized by lagged book assets), 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. Firm, industry-year, and rating fixed effects are included. R^2 does not include fixed effects. The sample period is 1980 to 2016. Standard errors clustered by firm and time are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A. Baseline Results

	CAPX Invest Rate		Inventory Invest Rate	
	(1)	(2)	(3)	(4)
Vol	-2.94***		-4.26***	
	(0.37)		(0.52)	
Vol × PPE liquidation recovery rate	2.84***			
	(1.02)			
Vol × Invt liquidation recovery rate			3.99***	
			(1.19)	
Abnormal vol (3-fac)		-3.15***		-4.47***
		(0.39)		(0.53)
Abnormal vol (3-fac) × PPE liquidation recovery rate		2.77**		
		(1.05)		
Abnormal vol (3-fac) × Invt liquidation recovery rate				4.02***
				(1.23)
Fixed effect	Firm, Industry-Year, Rating			
Obs	113,327	113,327	95,773	95,773
R^2	0.09	0.09	0.06	0.06

Panel B. Additional Results

	CAPX Invest Rate		Inventory Invest Rate	
	(1)	(2)	(3)	(4)
Vol	-3.61***		-3.86***	
	(0.44)		(0.77)	
Vol × PPE liquidation recovery rate	2.59**		-1.33	
	(1.04)		(1.66)	
Vol × Invt liquidation recovery rate	1.84**		4.08***	
	(0.88)		(1.17)	
Abnormal vol (3-fac)		-3.79***		-4.10***
		(0.45)		(0.79)
Abnormal vol (3-fac) × PPE liquidation recovery rate		2.52**		-1.25
		(1.07)		(1.68)
Abnormal vol (3-fac) × Invt liquidation recovery rate		1.77*		4.12***
		(0.87)		(1.21)
Fixed effect	Firm, Industry-Year, Rating			
Obs	113,327	113,327	95,773	95,773
R^2	0.09	0.09	0.06	0.06

Table 6: Asset Specificity and Impact of Macroeconomic Volatility: Cross-Country Evidence

This table presents industry-by-country regressions on how asset specificity affects the sensitivity of capital formation to macroeconomic volatility: $Y_{jkt} = \alpha_j + \beta\sigma_{kt} + \phi\lambda_j \times \sigma_{kt} + \gamma X_{jkt} + \epsilon_{jkt}$. The outcome variable is gross fixed capital formation per capita (in USD) in industry j and country k in columns (1) to (3), and industry j's share of gross fixed capital formation in country k in columns (4) and (6). Macro volatility σ_{kt} is the volatility of per capita real GDP growth in country k in the past 20 years. Asset specificity λ_j is the PPE liquidation recovery rate in each industry. We also control for industry-level PPE over assets (tangibility) and external finance dependence, measured following Rajan and Zingales (1995). We also control for log real GDP per capita and its interaction with all industry features. Columns (1), (2), (4), and (5) include industry fixed effects; columns (3) and (6) include industry-year and country-year fixed effects. R^2 does not include fixed effects. We use UNIDO data from 1996 to 2016, which records fixed capital formation by ISIC industries in each country. Standard errors clustered by country and industry-year are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

	Gross Fixed Capital Formation					
	Per Capita (USD)			Share		
	(1)	(2)	(3)	(4)	(5)	(6)
GDP growth vol	-11.64*	-11.63*		-0.17***	-0.17**	
	(6.54)	(6.77)		(0.05)	(0.07)	
GDP growth vol × PPE liquidation recovery rate	17.89***	35.19***	32.90***	0.39***	0.54***	0.49***
	(5.43)	(9.95)	(10.80)	(0.14)	(0.18)	(0.18)
GDP growth vol × PPE/assets		-25.82*	-22.09		-0.22	-0.15
		(15.32)	(14.85)		(0.30)	(0.27)
GDP growth vol × External finance dependence		0.10	0.13		0.00	0.00
		(0.08)	(0.11)		(0.00)	(0.00)
Industry fixed effect	Yes	Yes	/	Yes	Yes	/
Industry-year fixed effect	No	No	Yes	No	No	Yes
Country-year fixed effect	No	No	Yes	No	No	Yes
Obs	21,431	21,431	21,429	21,870	21,870	21,868
R^2	0.33	0.34	0.03	0.00	0.01	0.01

Table 7: Specificity of Fixed Assets and Rising Intangibles

This table shows the relationship between the specificity of fixed assets (PPE) and the rise of intangibles across firms in different industries. Columns (1) and (2) measure intangibles using BEA's estimates of intellectual property assets in each BEA industry. The outcome variable is the change of intellectual property as a share of fixed assets plus intellectual property from 1996 to 2016. Columns (3) and (4) use 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. The outcome variable is the change of intangibles as a share of intangibles and PPE from 1996 to 2016. Columns (2) and (4) instrument PPE liquidation recovery rates using predicted values based on PPE physical attributes ("IV" labeled "Yes"). Robust standard errors are presented in parentheses for columns (1) and (2), and standard errors clustered by industry are presented in parentheses for columns (3) and (4). Asterisks denote significance levels (***=1%, **=5%, *=10%).

	Intangible/(Intangible+Fixed Asset), 2016 minus 1996			
	BEA (Industry-Level)		Compustat (Firm-Level)	
	(1)	(2)	(3)	(4)
PPE liquidation recovery rate	-0.080**	-0.148**	-0.249***	-0.511**
	(0.033)	(0.072)	(0.095)	(0.217)
Constant	0.055***	0.078***	0.197***	0.284***
	(0.016)	(0.028)	(0.034)	(0.075)
IV	No	Yes	No	Yes
Obs	45	45	1,509	1,509
R^2	0.08	0.02	0.01	-0.00

Table 8: Intangibles, Asset Specificity, and Concentration

This table presents regressions where the outcome variable is the employment share by firms with over 500 employees in each four-digit NAICS industry every year from 1998 (start of this data) to 2016 in columns (1) to (3), and the revenue share by top 20 firms in each four-digit NAICS industry in every census year between 1997 and 2012 in columns (4) to (6). In columns (1) and (4), the independent variable is knowledge capital from the BEA fixed asset table, measured as R&D capital as a share of all fixed assets plus intangibles. In columns (2) and (5), the independent variable is knowledge capital among Compustat firms from Peters and Taylor (2017), measured as total R&D capital as a share of total fixed assets plus intangibles in each industry. In columns (3) and (6), the independent variable is the PPE liquidation recovery rate. Standard errors clustered by industry and time are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

	Large Firm Employment Share			Top 20 Firm Revenue Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Knowledge capital share (Census)	0.491***			0.348***		
	(0.087)			(0.085)		
Knowledge capital share (Compustat)		0.277*			0.243*	
		(0.157)			(0.127)	
PPE liquidation recovery rate			0.113			0.212*
			(0.120)			(0.109)
Constant	0.409***	0.480***	0.460***	0.416***	0.439***	0.381***
	(0.017)	(0.016)	(0.044)	(0.018)	(0.016)	(0.041)
Obs	5,341	4,456	4,134	872	878	845
R^2	0.06	0.01	0.00	0.04	0.01	0.01

Table 9: Asset Specificity and Vertical Integration: Cross-Country Evidence

This table presents industry-by-country regressions: $Y_{jk} = \alpha_j + \beta\sigma_k + \phi\lambda_j \times \sigma_k + \gamma X_{jk} + \epsilon_{jk}$. In columns (1) to (3), the outcome variable is the vertical integration index when the parent is downstream and subsidiaries are upstream. In columns (4) to (6), the outcome variable is the vertical integration index when the parent is upstream and subsidiaries are downstream. We use the rule of law index from the World Bank Governance Indicators. Asset specificity λ_j is the PPE liquidation recovery rate in the industry of the parent (main industry of the firm). We also control for industry-level PPE over assets (tangibility) and external finance dependence, measured following Rajan and Zingales (1995), as well as log real GDP per capita and the business sophistication index. Industry fixed effects and country fixed effects are included in columns (2), (3), (5), and (6). Columns (3) and (6) instrument PPE liquidation recovery rates using predicted values based on PPE physical attributes ("IV" labeled "Yes"). We use the 2012 BEA input-ouput table to construct the vertical integration index. Correspondingly, we use firms that are active in 2012 in ORBIS and measure the rule of law and other control variables using 2012 data. Country and industry fixed effects are inluded in columns (2), (3), (5), and (6). R^2 does not include fixed effects. Each industry corresponds to a four-digit industry in the BEA input-output table (similar to a four-digit NAICS industry) since we rely on the input-output table to calculcate the degree of vertical integration. Standard errors clustered by country and industry are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

	$S1$: Subsidiary Upstreamness			$S2$: Subsidiary Downstreamness		
	(1)	(2)	(3)	(4)	(5)	(6)
Rule of law	-0.014***			-0.015***		
	(0.004)			(0.004)		
PPE liquidation recovery rate	0.023			0.024		
	(0.026)			(0.029)		
Rule of law × PPE liquidation recovery rate	0.021***	0.013**	0.036**	0.021***	0.017***	0.041***
	(0.006)	(0.006)	(0.014)	(0.006)	(0.006)	(0.013)
PPE/assets	0.041***			0.052**		
	(0.015)			(0.021)		
External finance dependence	0.001*			0.000		
	(0.000)			(0.000)		
Rule of law × PPE/assets		0.005	0.003		0.006	0.004
		(0.004)	(0.004)		(0.004)	(0.004)
Rule of law × External finance dependence		-0.000	-0.000		0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Log GDP per capita	0.004*			0.004*		
	(0.002)			(0.002)		
Business sophistication index	0.010***			0.008***		
	(0.003)			(0.002)		
Country and industry fixed effect	No	Yes	Yes	No	Yes	Yes
IV	No	No	Yes	No	No	Yes
Obs	7,789	7,779	7,779	7,789	7,779	7,779
R^2	0.04	0.00		0.04	0.00	

Internet Appendix

IA1 Additional Figures and Tables

Figure IA1: PPE Liquidation Recovery Rates and Industry Conditions

This figure shows binscatter plots of PPE liquidation recovery rates for each case (y-axis) and industry leverage. The solid red dots represent observations from industries where the average PPE liquidation recovery rate is in the top tercile (industries with the most general PPE). The hollow blue dots represent observations from industries where the average PPE liquidation recovery rate is in the bottom tercile (industries with the most specific PPE).

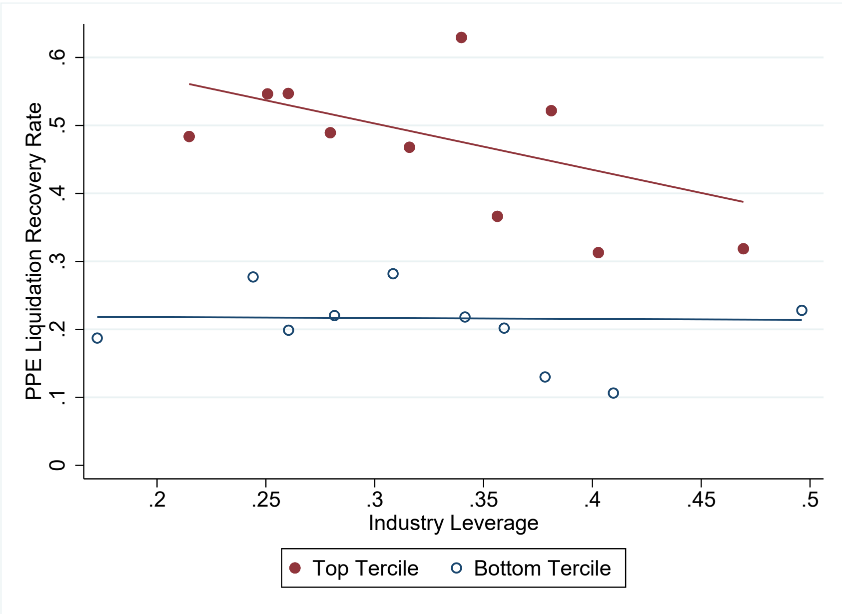
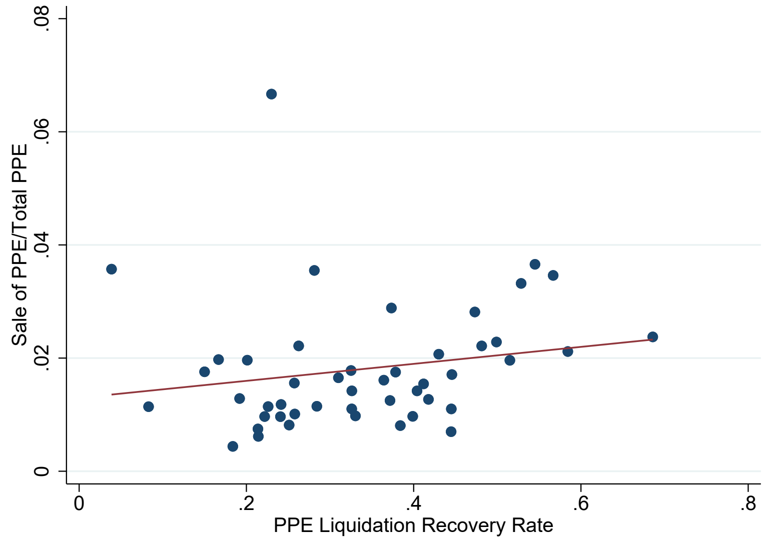


Figure IA2: PPE Liquidation Recovery Rates and Volume of PPE Sales

The y-axis is the industry-average PPE sale value (normalized by lagged net PPE). The x-axis is the industry-average PPE liquidation recovery rate in Panel A, and the value predicted by physical attributes (using column (1) of Table 3, Panel A) in Panel B. The sample period is 1996 to 2016.

Panel A. PPE Liquidation Recovery Rate and PPE Sale Amount



Panel B. PPE Liquidation Recovery Rate based on Physical Attributes and PPE Sale Amount

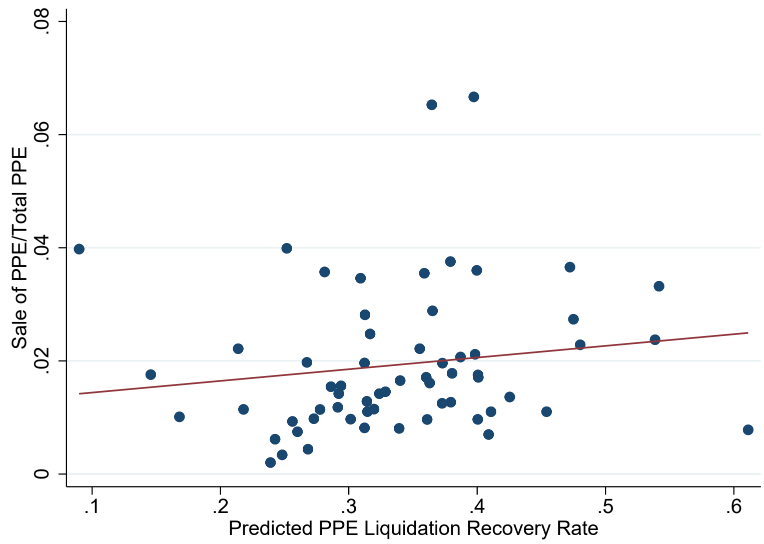


Figure IA3: Investment Irreversibility and Productivity Dispersion

This figure shows the relationship between MPK dispersion (y-axis) and the parameter of investment irreversibility ϵ in the model of Lanteri (2018) (x-axis). Lower ϵ means higher investment irreversibility. z is the productivity parameter, and we use two values of z as in Figure 5 of Lanteri (2018).

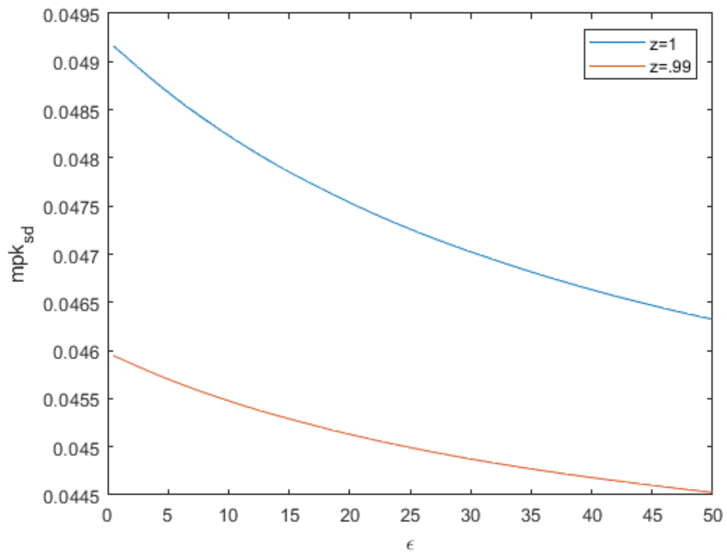
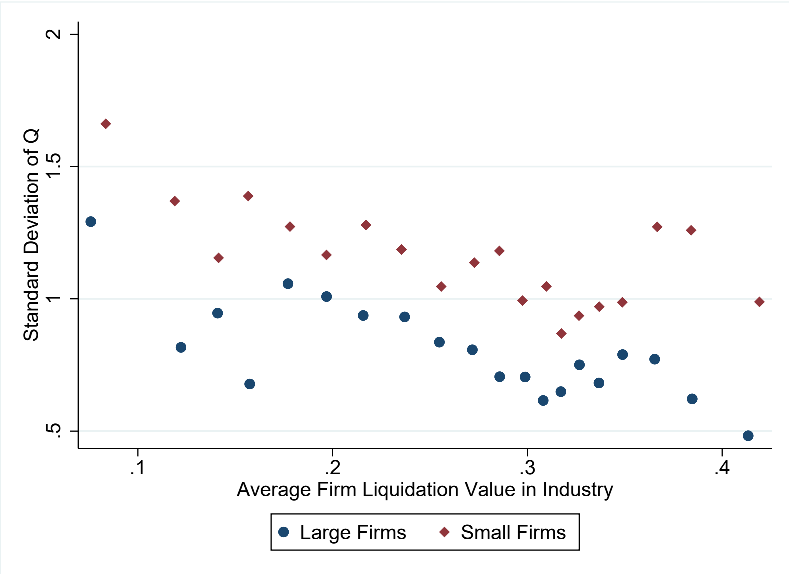


Figure IA4: Asset Specificity and Dispersion of Q

This figure shows binscatter plots of industry-level dispersion in Q. We calculate the cross-sectional standard deviation of Q for each two-digit SIC industry and each year. The x-axis is the industry-average firm liquidation value (including PPE and working capital, normalized by total book assets) constructed in Section 2.4. The y-axis is the average annual standard deviation in Q. In Panel A, Q is market value of assets (book assets minus book equity plus market value of equity) divided by book value of assets. In Panel B, Q is the estimate adjusted for intangibles from Peters and Taylor (2017). We calculate Q dispersion for large firms (assets above Compustat median in each year) and small firms (assets below Compustat median), and show binscatter plots for each group. The sample period is 1996 to 2016.

Panel A. Standard Average Q



Panel B. Q Adjusted for Intangibles (Peters and Taylor, 2017)

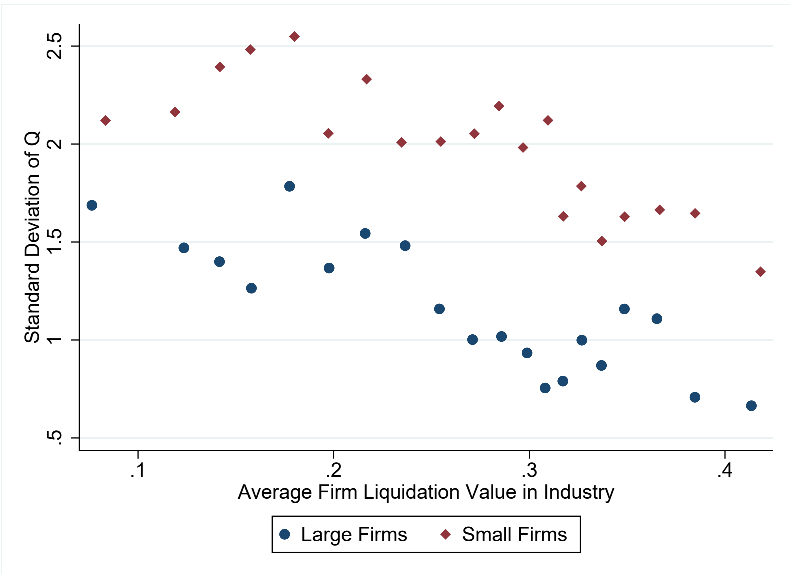
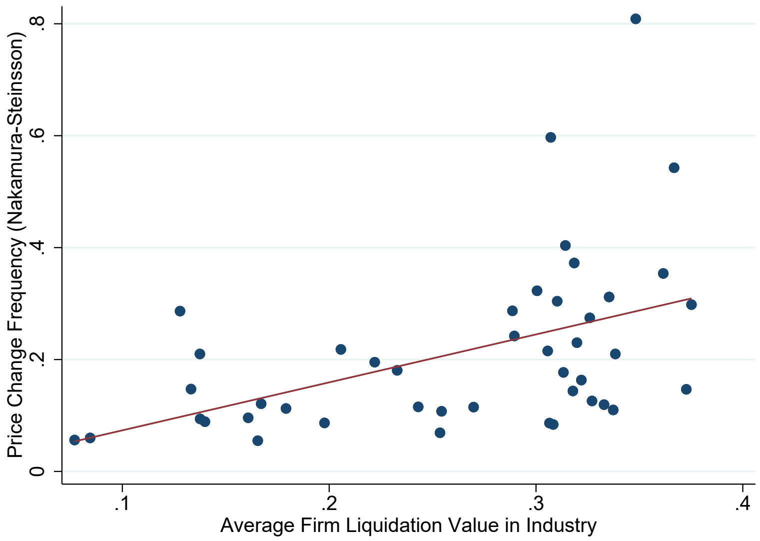


Figure IA5: Asset Specificity and Frequency of Price Change

This figure shows binscatter plots of the industry-level frequency of price change. The x-axis is the industry-average firm liquidation value (including PPE and working capital, normalized by total book assets) as constructed in Section 2.4. The y-axis is the industry-level frequency of price change (% per month), based on data from Nakamura and Steinsson (2008) in Panel A and Gorodnichenko and Weber (2016) in Panel B. Each industry is a two-digit SIC.

Panel A. Price Change Frequency in Nakamura and Steinsson (2008)



Panel B. Price Change Frequency in Gorodnichenko and Weber (2016)

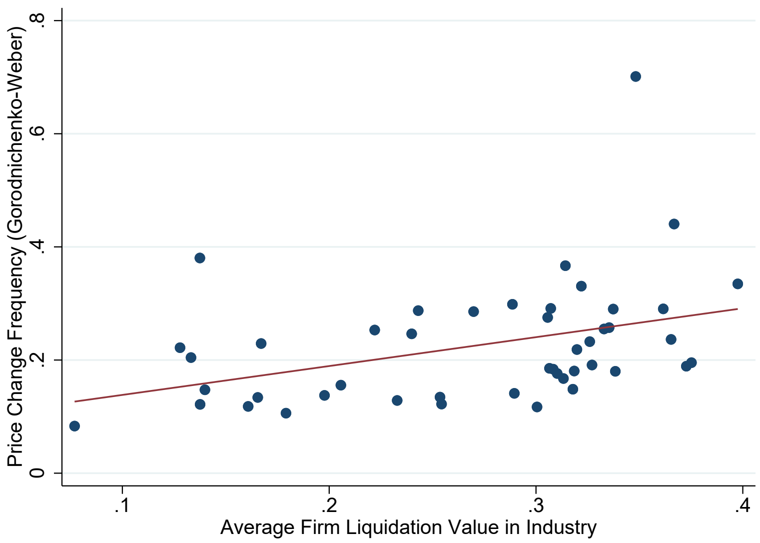


Table IA1: Liquidation Analysis Examples

Below are two examples of the liquidation analysis summary tables. Panel A comes from Lyondell Chemical (case number 09-10023). Panel B comes from Sorensen Communications (case number 14-10454).

Panel A. Lyondell Chemical

Obligor Debtors
Liquidation Analysis

Exhibi

(MILLIONS)	NBV	Low	High	Midpoint
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 & 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

Panel B. Sorenson Communications

Gross Assets Available for Distribution		**Unaudited Balances**	**Estimated Asset Recovery %**		**Estimated Recovery $**	
($ in 000's)	**Notes**	**Jan. 31, 2014**	**Low**	**High**	**Low**	**High**
Cash & Cash Equivalents	A	$ 94,596	100%	100%	$ 94,596	$ 94,596
Accounts Receivable	B	138,727	75%	100%	104,046	138,727
Prepaid and Other Current Assets	C	8,351	5%	10%	418	835
Property, Plant and Equipment, net	D	72,584	6%	12%	4,389	8,779
Goodwill, net	E	214,900	0%	0%	-	-
Intangible Assets	F	98,765	17%	50%	16,348	49,043
Other Assets, Miscellaneous	G	16,901	0%	3%	-	550
Income from Wind-Down Operations	H	-			-	30,276
Total Assets and Gross Proceeds		**$ 644,824**	**34%**	**50%**	**$ 219,796**	**$ 322,805**

Table IA2: Industry List

The table shows the number of cases in each two-digit SIC industry for which we can find liquidation recovery rates of receivable, inventory, or PPE. The cases are from the list of public Chapter 11 filings between 2000 and 2016 from BankruptcyData.com. We exclude financial firms (SIC between 6000 and 6999) and public administration (SIC greater than 9000). We have fewer observations for industries where public firms are rare such as construction contractors and building material retail (less than 10 to 20 firms in Compustat). We have many observations for large industries such as oil and gas, business services, and chemicals.

SIC2	Number of Cases
10 Metal Mining	5
12 Coal Mining	6
13 Oil/Gas Extraction	48
14 Quarrying-Nonmetals	2
15 Building Construction	3
17 Construction Contractors	1
20 Food Products	9
22 Textile Products	4
23 Apparel Products	4
24 Wood Products	2
25 Furniture and Fixtures	3
26 Paper Products	11
27 Printing and Publishing	19
28 Chemical Products	24
30 Rubber and Plastics Products	11
32 Stone, Clay, Glass, and Concrete	3
33 Primary Metal	10
34 Fabricated Metal Products	7
35 Machinery	7
36 Electronic Equipment	21
37 Transportation Equipment	19
38 Analytical Instruments	4
39 Misc. Manufacturing	6
41 Local Transit	2
42 Motor Freight	2
44 Water Transportation	8
45 Transportation by Air	9
47 Transportation Services	3
48 Communications	26
49 Electric and Gas	7
50 Wholesale Durables	2
51 Wholesale Non-Durables	5
52 Building Materials Dealers	1
53 General Merchandise Stores	3
54 Grocery Stores	3
55 Automotive Dealers	2
56 Apparel Stores	6
57 Furniture Stores	3
58 Restaurants	9
59 Misc. Retail	7
70 Lodging	7
72 Personal Services	2
73 Business Services	29
78 Motion Pictures	8
79 Amusement and Recreation	5
80 Health Services	7
82 Educational Services	1

Table IA3: Firm Characteristics and PPE Liquidation Recovery Rates

This table shows the relationship between firm characteristics and PPE liquidation recovery rates. In columns (1) and (2), the dependent variable is the case-level PPE liquidation recovery rate, using Chapter 11 liquidation recovery rate data. The independent variables include total liabilities over assets and size (log book assets) measured at filing, and EBITDA (normalized by lagged assets) from a merge with Compustat (we use latest annual results up to two years prior to filing). In columns (4) and (5), the dependent variable is the firm-level PPE sale recovery rate in Compustat data. Specifically, we compute the net book value of PPE sold based on lagged net book value of PPE plus capital expenditures minus depreciation minus current net book value of PPE. We exclude firm-years with mergers and spinoffs, where it is difficult to tease out the change in PPE book value due to these events. We compute the PPE sale recovery rate using PPE sale proceeds divided by the net book value of PPE sold. The independent variables include book leverage (total debt over total assets), size (log book assets), and EBITDA. Industry fixed effects are included. R^2 does not include fixed effects. Standard errors clustered by industry and time are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

	Liquidation Recovery Rate		Sale Recovery Rate	
	(1)	(2)	(3)	(4)
Total liabilities/assets	-0.002	0.018		
	(0.015)	(0.028)		
Book leverage			0.161	0.222
			(0.187)	(0.193)
EBITDA/l.assets		0.108*		0.165
		(0.058)		(0.118)
Log assets	-0.008	0.002	-0.110***	-0.127***
	(0.009)	(0.015)	(0.027)	(0.030)
Fixed effect	Industry			
Obs	336	195	9,459	9,421
R^2	0.21	0.30	0.01	0.01

Table IA4: Economic Conditions and Equipment Auction Values

This table uses equipment auction values analyzed by Murfin and Pratt (2019) and studies the impact of macroeconomic conditions (measured using past 12-month real GDP growth) in Panel A and industry conditions (measured using industry leverage) in Panel B. In Panel A, we use the auction recovery rate in columns (1) and (2), namely auction value normalized by estimated net book value (using original price and quadratic depreciation following Ramey and Shapiro (2001)); this variable is mainly available for a subset of construction equipment for which we can find data on the original price for each vintage and equipment manufacturer-model in order to calculate the net book value. We use log auction value in columns (3) to (6), for both construction equipment and other equipment (agriculture, tractor, and truck). In Panel B, we use the auction recovery rate in columns (1) and (2) and log auction value in columns (3) to (6), focusing on construction equipment. For industry leverage, we use the average book leverage in construction industries (two-digit SICs from 15 to 17). "Basic" fixed effect includes Manufacturer×Type, Age×Type, Quarter×Type, and Condition. "Additional" fixed effect includes Manufacturer×Type×Age×Condition and Quarter×Type. The sample period is 1994 to 2013. R^2 does not include the fixed effects. Standard errors clustered by manufacturer-equipment type and year are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%). We are grateful to Justin Murfin for generously helping with the analysis.

Panel A. Relationship with Macroeconomic Conditions

	Auction Recovery Rate		Log Auction Value			
	(1)	(2)	(3)	(4)	(5)	(6)
GDP growth	1.79***	1.76***	2.35***	2.52***	2.49***	2.43***
	(0.38)	(0.36)	(0.58)	(0.56)	(0.53)	(0.51)
Equipment type	Construction				Agriculture, Tractor, Truck	
Fixed effect	Basic	Additional	Basic	Additional	Basic	Additional
Obs	86,808	85,300	264,776	256,299	413,489	404,201
R^2	0.027	0.026	0.025	0.030	0.019	0.021

Panel B. Relationship with Industry Conditions

	Auction Recovery Rate		Log Auction Value	
	(1)	(2)	(3)	(4)
Industry leverage	-0.47**	-0.46**	-0.64**	-0.65**
	(0.18)	(0.18)	(0.28)	(0.27)
Equipment type	Construction			
Fixed effect	Basic	Additional	Basic	Additional
Obs	86,808	85,300	264,776	256,299
R^2	0.015	0.014	0.023	0.027

Table IA5: Q Dispersion

This table shows industry-level regressions where the outcome variable is average annual cross-sectional dispersion in Q for each two-digit SIC industry. Q is market value of assets (book value of assets minus book equity plus market value of equity) over book value of assets in columns (1) to (3), and Q adjusted for intangibles from Peters and Taylor (2017) in columns (4) to (6). The independent variable is the average firm-level liquidation value (including PPE and working capital) constructed in Section 2.4 in each industry. The sample period is 1996 to 2016. Each industry is a two-digit SIC. Robust standard errors are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

	Standard Q			Adjusted Q		
	All (1)	Large (2)	Small (3)	All (4)	Large (5)	Small (6)
Ind-avg firm liquidation value	-2.15***	-1.91***	-2.06***	-3.42***	-3.69***	-2.57*
	(0.57)	(0.58)	(0.71)	(1.25)	(0.88)	(1.49)
Obs	47	47	47	47	47	47
R^2	0.25	0.22	0.09	0.18	0.29	0.08

Table IA6: Price Rigidity

This table presents industry-level regressions where the outcome variable is the industry-level frequency of price change (% per month), based on data from Nakamura and Steinsson (2008) in columns (1) and (2) and Gorodnichenko and Weber (2016) in columns (3) and (4). The independent variables include PPE liquidation recovery rates, inventory liquidation recovery rates, and industry-average firm liquidation values (including PPE and working capital, normalized by total book assets) as constructed in Section 2.4. Each industry is a two-digit SIC. Robust standard errors are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

	Frequency of Price Change in Industry			
	Nakamura-Steinsson		Gorodnichenko-Weber	
	(1)	(2)	(3)	(4)
PPE liquidation recovery rate	0.08		0.07	
	(0.18)		(0.13)	
Inventory liquidation recovery rate	0.39***		0.16*	
	(0.11)		(0.09)	
Ind-avg firm liquidation value		0.86***		0.51***
		(0.23)		(0.18)
Constant	0.02	-0.01	0.13***	0.09*
	(0.05)	(0.05)	(0.05)	(0.05)
Obs	44	44	46	46
R^2	0.16	0.22	0.06	0.15

IA2 Liquidation Analysis Examples

Table IA1 shows an example of the liquidation analysis summary table from Lyondell Chemical. In the following, we present excerpts of detailed additional discussions in the Lyondell case, which explain the procedures for the liquidation value estimates of PPE, inventory, account receivable, and cash.

Figure IA6: Lyondell Chemical Example: Plant-Level Information for All PPE

This figure shows an excerpt of discussions about PPE liquidation value estimates in the liquidation analysis by Lyondell (Panel A) and an excerpt of the plant-level liquidation value estimates reported in an appendix prepared by American Appraisal Associates (Panel B).

Panel A. Excerpt of PPE Discussion in Liquidation Analysis

Property, Plant, and Equipment ("PP&E")

- PP&E includes all owned land, land improvements and buildings, battery limit process units, off sites, support assets and construction in progress.
- Appendix I is a report prepared by American Appraisal Associates, Inc. that includes projected liquidation values of PP&E as of April 1, 2010 that were used for this Liquidation Analysis.

Panel B. Excerpt of Plant-Level Estimate in Liquidation Analysis Appendix

PLANT CODE	PLANT NAME	LOCATION	SEGMENT	GRAND TOTAL
CHEMICALS SEGMENT				
4102	BASELL MEXICO	POLYOLEFINAS MEXICO	CHEMICALS	973,000
4100	BASELL MEXICO	BASELL MEXICO	CHEMICALS	21,000
BCO	BAYPORT EO	PASADENA, TX	CHEMICALS	23,875,000
BLO	BAYPORT PO @ 17.4% OWNERSHIP	PASADENA, TX	CHEMICALS	12,388,000
	BERRE	BERRE, FRANCE	CHEMICALS	24,442,000
RBO	BOTLEK	BOTLEK, NETHERLANDS	CHEMICALS	138,328,000
CIO	BRUNSWICK	BRUNSWICK, GA	CHEMICALS	4,415,000
CHO	CHANNELVIEW - NORTH	CHANNELVIEW, TX	CHEMICALS	155,927,000
CXO	CHANNELVIEW - SOUTH	CHANNELVIEW, TX	CHEMICALS	18,801,000
CXO	CHANNELVIEW SOUTH- PO/SM 2	CHANNELVIEW, TX	CHEMICALS	26,252,000
CVOX	CHANNELVIEW SOUTH- PO/SM 1 @ 17.4% OWNERSHIP	CHANNELVIEW, TX	CHEMICALS	3,721,000
CXO	CHANNELVIEW SOUTH- BDO	CHANNELVIEW, TX	CHEMICALS	9,211,000
CLO	CLINTON	CLINTON, IA	CHEMICALS	41,805,000
FLO	FOS-SUR-MER	FOS-SUR-MER, FRANCE	CHEMICALS	45,974,000
CCO	CORPUS CHRISTI	CORPUS CHRISTI, TX	CHEMICALS	88,349,000
0	VERENNES	VERENNES	CLOSED	0
JAX	JACKSONVILLE	JACKSONVILLE, FL	CHEMICALS	9,067,000
LPO	LA PORTE	LA PORTE, TX	CHEMICALS	64,340,000
LAO	LA PORTE ACETYLS	LA PORTE, TX	CHEMICALS	31,798,000
RMO	MAASVLATKTE @ 50% OWNERSHIP	MAASVLATKTE, NETHERLANDS	CHEMICALS	32,486,000
MIO	MORRIS	MORRIS, IL	CHEMICALS	24,638,000
1001	MUENCHSMUENSTER	MUENCHSMUENSTER, GERMANY	CHEMICALS	46,524,000
NEO	NEWARK	NEWARK, NJ	CHEMICALS	336,000
CBP	PIPELINE	MARKHAM-MONT BELVIEU, TX	CHEMICALS	98,163,000
TCO	TUSCOLA	TUSCOLA, IL	CHEMICALS	5,296,000
1001	WESSELING	KNAPSACK, GERMANY	CHEMICALS	409,707,000
TOTAL CHEMICALS SEGMENT				**1,316,837,000**

Lyondell Chemical Example: Plant-Level Information for All PPE (Cont.)

PLANT CODE	PLANT NAME	LOCATION	SEGMENT	GRAND TOTAL
POLYMERS SEGMENT				
	BASELL POLYOLEFINS KOREA	SEOUL, ROK	POLYMERS	0
BYO	BAYPORT POLYMER	PASADENA, TX	POLYMERS	36,765,000
1000	BAYREUTH	BAYREUTH, GERMANY	POLYMERS	16,938,000
	BERRE	BERRE, FRANCE	POLYMERS	110,074,000
1301	BRINDISI	BRINDISI, ITALY	POLYMERS	76,841,000
1201	CARRINGTON	CARRINGTON, UK	POLYMERS	10,848,000
CBO	CHOCOLATE BAYOU POLYMERS	ALVIN, TX	POLYMERS	28,853,000
CLO	CLINTON	CLINTON, IA	POLYMERS	96,414,000
4005	EDISON	EDISON, NJ	POLYMERS	8,717,000
FPO	FAIRPORT	FAIRPORT, OH	POLYMERS	1,714,000
1300	FERRARA	FERRARA, ITALY	POLYMERS	30,654,000
1001	FRANKFURT	FRANKFURT, GERMANY	POLYMERS	16,278,000
4005	JACKSON	JACKSON, TN	POLYMERS	6,398,000
1001	KNAPSACK	KNAPSACK, GERMANY	POLYMERS	44,376,000
LPO	LA PORTE	LA PORTE, TX	POLYMERS	44,115,000
LKO	LAKE CHARLES POLYMER	LAKE CHARLES, LA	POLYMERS	43,770,000
2100	CLYDE PP	CLYDE, AUSTRALIA	POLYMERS	8,102,000
3110	GEELONG LABORATORY	GEELONG, AUSTRALIA	POLYMERS	22,000
3100	GEELONG PP	GEELONG, AUSTRALIA	POLYMERS	19,186,000
3000	MELBOURNE OFFICE	MELBOURNE, AUSTRALIA	POLYMERS	282,000
5000	PETROKEN	ENSENADA, ARGENTINA	POLYMERS	13,923,000
5100	PINDA	PINDA, BRAZIL	POLYMERS	343,000
4014	MANSFIELD	MANSFIELD, TX	POLYMERS	9,443,000
MTO	MATAGORDA	MATAGORDA, TX	POLYMERS	86,656,000
1201	MILTON KEYNES	MILTON KEYNES, UK	POLYMERS	8,532,000
1400	MOERDIJK	MOERDIJK, NETHERLANDS	POLYMERS	38,669,000
MIO	MORRIS	MORRIS, IL	POLYMERS	74,834,000
1001	MUENCHSMUENSTER	MUENCHSMUENSTER, GERMANY	POLYMERS	112,442,000
1601	TARRAGONA	TARRAGONA, SPAIN	POLYMERS	27,076,000
1300	TERNI	TERNI, ITALY	POLYMERS	37,679,000
VTO	VICTORIA	VICTORIA, TX	POLYMERS	24,349,000
8505	BAP GUANGZHOU	GUANGZHOU, PRC	POLYMERS	3,027,000
8503	BAP SUZHOU	SUZHOU, PRC	POLYMERS	2,876,000
8000	BAP THAILAND	BANGKOK, THAILAND	POLYMERS	3,777,000
8500	BASELL ASIA PACIFIC	HONG KONG, PRC	POLYMERS	13,000
LJI	LYONDELL JAPAN	TOKYO, JAPAN	POLYMERS	3,000
SIN	LYONDELL SOUTH ASIA	SINGAPORE	POLYMERS	1,000
TOTAL POLYMERS SEGMENT				**1,043,990,000**

Figure IA7: Lyondell Chemical Example: Other Assets

This figure shows an excerpt of discussions about the liquidation value estimates of inventory, receivable, and cash in the liquidation analysis of Lyondell.

Panel A. Excerpt of Discussions about Inventory

Inventory

- The Debtors' inventories are comprised of raw materials, work-in-process ("WIP") and finished goods, as well as supplies and materials.
- Types of inventory products include polymers (polyethylene and polypropylene), chemicals (ethylene and propylene), and refining products (such as gasoline, diesel, and jet fuel).
- The recovery analysis was performed by reviewing the external field examination and bank appraisal by entity for the period ending September 30, 2009, which was in effect at the end of 2009.
- The September 30, 2009 gross recovery advance rates for raw materials, WIP and finished goods were discounted by approximately 7% for ineligibles to reflect the recovery ranges for each entity whose inventory secures bank financing.
- The "supplies and materials" component of inventory is assumed to have a recovery range of 50% to 75% for all entities.
- The recovery ranges vary by entity and type of inventory, as presented in the table below.
- The products produced in EAI are primarily polymers and chemicals, and the inventory liquidation assumptions for EAI approximate those of Basell USA Inc.

	Lyondell Chemical Company	Basell USA Inc.	Equistar Chemicals, LP	Houston Refining LP	Millennium Petrochemicals, Inc. (Virginia)
Raw Materials	68.7% - 78.7%	60.9% - 70.9%	69.9% - 79.9%	71.6% - 81.6%	57.3% - 67.3%
Work-In-Process	54.5% - 64.5%	68.7% - 78.7%	64.7% - 74.7%	67.6% - 77.6%	57.3% - 67.3%
Finished Goods	67.3% - 77.3%	68.7% - 78.7%	79.6% - 89.6%	67.6% - 77.6%	73.2% - 83.2%

Panel B. Excerpt of Discussions about Cash and Receivable

Cash and Cash Equivalents and Short-Term Investments

- The Liquidation Analysis assumes that operations during the liquidation period would not generate additional cash available for distribution except for net proceeds from the disposition of non-cash assets.
- The liquidation value for all entities is estimated to be approximately 100% of the net book value as of December 31, 2009.

Trade Accounts Receivable

- The analysis of accounts receivable assumes that a chapter 7 trustee would retain certain existing staff of the Debtors to handle an aggressive collection effort for outstanding trade accounts receivable for the entities undergoing an orderly liquidation.
- Collectible accounts receivable are assumed to include all third-party trade accounts receivable.
- A range of discount factors based on the January 1, 2010 U.S. asset backed facilities effective advance rates were applied to receivables to estimate liquidation values.
- Collections during a liquidation of the Debtors may be further compromised by likely claims for damages for breaches of (or the likely rejection of) customer contracts, and attempts by customers to set off outstanding amounts owed to the Debtors against such claims.
- The liquidation values of trade accounts receivable were estimated at 60.0% to 70.0% of the net book value as of December 31, 2009 for purposes of this Liquidation Analysis.

IA3 Measuring Physical Attributes of PPE

In this appendix, we further explain the measurement of the physical attributes of property, plant, and equipment (PPE). As described in Section 3.1, we utilize information from the BEA's fixed asset table and input-output table. First, we collect information on the composition of fixed assets in each industry from the BEA's fixed asset table, which shows the stock of 71 types of fixed assets in 58 BEA industries each year. Second, we measure the attributes of each of the 71 types of assets, using information from the BEA's input-output table. Finally, we construct the overall industry-level attributes based on the share of each asset in an industry's fixed asset stock. The 71 types of fixed assets are listed in Table IA7.

Table IA7: List of Assets in the BEA Fixed Asset Table

This table shows the 71 types of assets in the BEA fixed asset table.

	Code	Equipment		Code	Structure
1	EP1A	**Mainframes**	40	SOO1	**Office**
2	EP1B	**PCs**	41	SB31	**Hospitals**
3	EP1C	**DASDs**	42	SB32	**Special care**
4	EP1D	**Printers**	43	SOO2	**Medical buildings**
5	EP1E	**Terminals**	44	SC03	**Multimerchandise shopping**
6	EP1F	**Tape drives**	45	SC04	**Food and beverage establishments**
7	EP1G	**Storage devices**	46	SC01	**Warehouses**
8	EP1H	**System integrators**	47	SOMO	**Mobile structures**
9	EP20	**Communications**	48	SC02	**Other commercial**
10	EP34	**Nonelectro medical instruments**	49	SI00	**Manufacturing**
11	EP35	**Electro medical instruments**	50	SU30	**Electric**
12	EP36	**Nonmedical instruments**	51	SU60	**Wind and solar**
13	EP31	**Photocopy and related equipment**	52	SU40	**Gas**
14	EP12	**Office and accounting equipment**	53	SU50	**Petroleum pipelines**
15	EI11	**Nuclear fuel**	54	SU20	**Communication**
16	EI12	**Other fabricated metals**	55	SM01	**Petroleum and natural gas**
17	EI21	**Steam engines**	56	SM02	**Mining**
18	EI22	**Internal combustion engines**	57	SB10	**Religious**
19	EI30	**Metalworking machinery**	58	SB20	**Educational and vocational**
20	EI40	**Special industrial machinery**	59	SB41	**Lodging**
21	EI50	**General industrial equipment**	60	SB42	**Amusement and recreation**
22	EI60	**Electric transmission and distribution**	61	SB43	**Air transportation**
23	ET11	**Light trucks (including utility vehicles)**	62	SB45	**Other transportation**
24	ET12	**Other trucks, buses and truck trailers**	63	SU11	**Other railroad**
25	ET20	**Autos**	64	SU12	**Track replacement**
26	ET30	**Aircraft**	65	SB44	**Local transit structures**
27	ET40	**Ships and boats**	66	SB46	**Other land transportation**
28	ET50	**Railroad equipment**	67	SN00	**Farm**
29	EO11	**Household furniture**	68	SO01	**Water supply**
30	EO12	**Other furniture**	69	SO02	**Sewage and waste disposal**
31	EO30	**Other agricultural machinery**	70	SO03	**Public safety**
32	EO21	**Farm tractors**	71	SO04	**Highway and conservation and development**
33	EO40	**Other construction machinery**			
34	EO22	**Construction tractors**			
35	EO50	**Mining and oilfield machinery**			
36	EO60	**Service industry machinery**			
37	EO71	**Household appliances**			
38	EO72	**Other electrical**			
39	EO80	**Other**			

To measure the mobility and customization of each of the 71 types of assets, we collect transportation cost and design cost information from the BEA's input-output table. To find counterparts of the 71 types of fixed assets in the input-output table, we use the PEQ bridge for equipment and match by hand for structures. Both the input-output table and the fixed asset table are from 1997.

- For transportation costs, we start with the input-output "use" table. For each asset, we find all the entries where it is an input (i.e., recorded as a "commodity") and accordingly transported from its producers to users. We calculate the total transportation costs and divide by the total value of the asset used (in producer prices). In other words, we calculate the transportation cost as a share of the total asset value. For instance, if the asset is cars, then we calculate the transportation costs of cars between producers and users and normalize by the total production costs of cars.

- For design costs, we also start with the input-output "use" table. For each asset, we find the entries where it is an output and calculate the share of design costs in the total costs of producing it. We categorize costs related to design and customization using the following types of inputs: "design," "custom computer programming," "information services," "data processing services," "research," "advertising," "management consulting," "business support services," and "miscellaneous professional and technical services." For instance, if the asset is cars, then we calculate the share of design and related costs in the total production costs of cars.[29]

For each industry in the BEA fixed asset table, we compute the overall transportation costs and design costs by summing up the asset-level attributes, weighting each asset based on its share in the industry's fixed asset stock. Accordingly, the industry-level transportation cost measure captures the total transportation cost of all fixed assets in an industry as a share of their total production cost. Similarly, the industry-level customization measure captures the total design cost of all fixed assets in an industry as a share of their total production cost. Finally, we match the industries in the BEA fixed asset table with two-digit SIC industries in our liquidation recovery rate data. The matching is listed below in Table IA8.

For durability, we can directly calculate the average depreciation rate in each two-digit SIC industry using Compustat. Because Compustat firms primarily use a linear depreciation method, we calculate the depreciation rate using annual depreciation (Compustat variable DP minus variable AM) divided by lagged gross PPE (Compustat variable PPEGT).

Table IA9 presents industry-level (two-digit SIC industries) summary statistics of the physical attributes: mobility (transportation cost as a share of PPE production cost), durability (depreciation rate), customization (design cost share in PPE production cost). It also shows statistics for the share of PPE in an industry that is designated firm-specific; each of the 71 types of assets in the BEA fixed asset table is designated firm-specific if the customization measure is in the top tercile.

[29] Alternatively, we can also measure the cost of design using the share of production costs that are not associated with purchasing materials. Specifically, to produce assets that are not custom designed, a larger fraction of the costs may come directly from purchasing material (costs of goods sold in accounting statements, or COGS). Accordingly, for each of the 71 types of assets, we can find the industry that produces it and calculate the fraction of COGS in the total production costs in that industry (e.g., for cars, we can calculate the share of COGS in the total operating costs of car producers). A higher share of COGS in producing an asset means less design and customization. Results are similar for this alternative measure.

Table IA8: List of Industries in the BEA Fixed Asset Table

This table shows the industries in the BEA fixed asset table, and the closest corresponding two-digit SICs.

INDUSTRY TITLE	BEA CODE	Two-Digit SIC
Agriculture, forestry, fishing, and hunting	———	
Farms	110C	1, 2, 7
Forestry, fishing, and related activities	113F	8, 9, 24
Mining	———	
Oil and gas extraction	2110	13
Mining, except oil and gas	2120	10, 12, 14
Support activities for mining	2130	10, 12–14
Utilities	**2200**	**19**
Construction	**2300**	**15–17**
Manufacturing	———	
Durable goods	———	
Wood products	3210	24
Nonmetallic mineral products	3270	32
Primary metals	3310	33
Fabricated metal products	3320	34
Machinery	3330	35, 38
Computer and electronic products	3340	35, 36, 38
Electrical equipment, appliances, and components	3350	36
Motor vehicles, bodies and trailers, and parts	336M	37
Other transportation equipment	336O	37
Furniture and related products	3370	24, 25
Miscellaneous manufacturing	338A	38, 39
Nondurable goods	———	
Food, beverage, and tobacco products	311A	20, 21
Textile mills and textile product mills	313T	22, 23
Apparel and leather and allied products	315A	23, 31
Paper products	3220	26
Printing and related support activities	3230	27
Petroleum and coal products	3240	29
Chemical products	3250	28
Plastics and rubber products	3260	30
Wholesale trade	**4200**	50, 51
Retail trade	**44RT**	52–59
Transportation and warehousing	———	
Air transportation	4810	45
Railroad transportation	4820	40
Water transportation	4830	44
Truck transportation	4840	42
Transit and ground passenger transportation	4850	41
Pipeline transportation	4860	46
Other transportation and support activities	487S	47
Warehousing and storage	4930	42
Information	———	
Publishing industries (including software)	5110	27, 87
Motion picture and sound recording industries	5120	78
Broadcasting and telecommunications	5130	48
Information and data processing services	5140	73
Real estate and rental and leasing	———	
Real estate	5310	65
Rental and leasing services and lessors of intangible assets	5320	65, 67, 73, 75, 78
Professional, scientific, and technical services	———	
Legal services	5411	81
Computer systems design and related services	5415	73
Miscellaneous professional, scientific, and technical services	5412	72, 73, 87
Management of companies and enterprises	**5500**	
Administrative and waste management services	———	
Administrative and support services	5610	73
Waste management and remediation services	5620	49
Educational services	**6100**	82
Health care and social assistance	———	
Ambulatory health care services	6210	80
Hospitals	622H	80
Nursing and residential care facilities	6230	80
Social assistance	6240	83
Arts, entertainment, and recreation	———	
Performing arts, spectator sports, museums, and related activities	711A	84
Amusements, gambling, and recreation industries	7130	79
Accommodation and food services	———	
Accommodation	7210	70
Food services and drinking places	7220	58
Other services, except government	**8100**	72, 75, 76, 86

Table IA9: Summary Statistics of PPE Physical Attributes

This table shows the mean, standard deviation, and quartiles of industry-level PPE physical attributes. It also shows statistics of the fraction of PPE that is not firm-specific in an industry. Each industry is a two-digit SIC.

Variable	mean	p25	p50	p75	s.d.
Transportation cost	0.515	0.388	0.481	0.664	0.204
Depreciation rate	0.142	0.095	0.129	0.182	0.062
Design cost share	0.016	0.013	0.017	0.019	0.004
Industry size (sales share)	0.014	0.001	0.005	0.019	0.019
Fraction PPE non-firm specific	0.649	0.506	0.633	0.825	0.179

IA4 Attributes and Liquidation Recovery Rates of Inventory

We measure the physical attributes of inventory in different industries along the following dimensions. The first attribute is durability, or shelf life (some inventories are perishable such as restaurants' fresh food inventory). The second and third attributes are mobility and customization, similar to the observations in Section 3.1 for PPE. The final attribute is the share of work-in-progress inventory, which is generally not redeployable. As before, we measure industry-level attributes for each two-digit SIC industry and use all data from 1997.

We measure inventory durability/shelf life using the ratio of inventory stock to inventory spending for firms in each industry in Compustat. When inventory is perishable, most inventory needs to be purchased during the same period, instead of being stocked for future use, so the inventory stock should be small relative to inventory spending. Industries with the longest shelf life include construction, instrument manufacturing, auto dealers, and furniture stores. Industries with the shortest shelf life include restaurants, recreational services, transportation services, and utilities.

We measure inventory mobility using transportation cost data from the BEA input-output table, similar to the analysis for PPE in Section 3.1. We start by calculating the transportation cost (relative to total production cost) for each commodity in the input-output table. Since inventory includes both raw materials and finished goods, we calculate the transportation costs of both the input and the output for each 4-digit input-output table industry (which can be mapped to a four-digit NAICS industry). The transportation costs associated with an industry's input (output) correspond to the mobility of its raw materials (finished goods). We merge the transportation cost of raw materials and final goods into Compustat (based on four-digit NAICS), and then calculate the overall transportation cost of inventory in an industry using the shares of its inventory accounted for by raw materials and final goods (available in Compustat data). In this way, we construct the inventory mobility measure for each two-digit SIC through the combination of the BEA input-output table and Compustat. Industries with the highest inventory mobility include electronic manufacturing, recreational services, health services, and cinemas. Industries with the lowest inventory mobility include construction, mining, and concrete manufacturing.

We measure inventory customization using the share of design cost in total production cost based on the BEA input-output table, also similar to the analysis for PPE in Section 3.1. We start by calculating the design cost share for each commodity in the input-output table. For each four-digit input-output table industry, we calculate the design cost share associated with producing its inputs as the customization of raw materials, and calculate the design cost share in producing its output as the customization of finished goods. We merge the design cost of raw materials and final goods into Compustat (based on the four-digit NAICS), and then calculate the overall design cost of inventory in an industry using the shares of its inventory accounted for by raw materials and final goods. Again, in this way, we construct the inventory customization measure for each two-digit SIC through the combination of the BEA input-output table and Compustat. Industries with the lowest degree of customization include mining, construction, wood product manufacturing, and utilities. Industries with the highest degree of customization include shipping, communications, chemical manufacturing, and instrument manufacturing.

Finally, we measure the share of work-in-progress inventory in total inventory for Compustat firms, and take the average for each two-digit SIC industry.

Table IA10, Panel A, shows industry-level summary statistics of inventory physical attributes. Table IA10, Panel B, shows the relationship between inventory physical attributes in an industry and the industry-level inventory liquidation recovery rate. Since inventory in certain industries is fairly perishable (e.g., fresh food inventory of restaurants), shelf life can be a primary issue. We find that when inventory is perishable, mobility and customization matter less (perishable inventory is difficult to redeploy in any case). When inventory is more durable, on the other hand, mobility and customization matter more. In addition, having a higher share of work-in-progress inventory is associated with a slightly lower inventory liquidation recovery rate. The impact of industry size (the industry's sales as a share of total sales in Compustat) is weakly positive like before, as shown in column (2).

Connections with Rauch (1999). Rauch (1999) provides a classification of internationally traded commodities based on whether they are traded on organized exchanges. This classification has been used as a proxy for specificity (Nunn, 2007). Since these commodities are most closely related to goods categorized as inventory, we explore connections with the Rauch (1999) data below.

In Table IA11, we look at how the physical attributes of inventory relate to the Rauch (1999) measure. In particular, starting with the original Rauch (1999) data with four-digit SITC codes, we convert these codes to industry codes in the 1997 BEA input-output table following the procedure in Nunn (2007). For each commodity in the input-output table (e.g., poultry, iron ore, paper, cereal), we have an indicator variable that equals one if it is classified as traded on organized exchanges according to Rauch (1999). In columns (1) and (2), we use commodity-level data to study the relationship between the exchange trading indicator variable and the customization and mobility of the commodity. In addition, for each industry, we use the Rauch (1999) data at the commodity level combined with the BEA input-output table to calculate the extent to which its input (raw materials) and output (finished goods) are exchange-traded. We then use Compustat data to assess the extent to which the overall inventory in an industry is exchange-traded, based on the shares of raw materials and final goods. In columns (3) and (4), we use industry-level data to study the relationship between the fraction of exchange-traded commodities in the overall inventory of an industry and the overall customization, mobility, and shelf life of inventory.

The results in Table IA11 show that when goods are more customized (higher design cost share), they are significantly less likely to be traded on organized exchanges. There is also a negative but weaker relationship between transportation cost and exchange trading. Finally, because the Rauch (1999) data covers commodities that are internationally traded to begin with, shelf life is less important for this set of goods.

Table IA10: Industry-Level Physical Attributes of Inventory

Panel A shows the mean, standard deviation, and quartiles of industry-level inventory physical attributes. The physical attributes are calculated using the BEA input-output flow table and Compustat data in 1997. Panel B shows the relationship between the industry-average inventory liquidation recovery rate and physical attributes of inventory in the industry. Each industry is a two-digit SIC. Robust standard errors are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A. Summary Statistics

Variable	mean	p25	p50	p75	s.d.
Work-in-progress share	0.087	0.004	0.032	0.117	0.145
Shelf life	0.232	0.099	0.186	0.302	0.192
Transportation cost	0.084	0.009	0.020	0.043	0.203
Design cost share	0.027	0.021	0.028	0.033	0.012

Panel B. Relationship with Inventory Liquidation Recovery Rate

	Inventory Liquidation Recovery Rate	
	(1)	(2)
Shelf life	1.983**	2.156**
	(0.788)	(0.814)
Transportation cost	0.231	0.285
	(0.217)	(0.228)
Shelf life × Transportation cost	-1.757**	-1.908***
	(0.679)	(0.699)
Design cost share	6.077	6.952
	(4.252)	(4.562)
Shelf life × Design cost share	-39.795*	-45.032**
	(20.178)	(21.170)
Work-in-progress share	-0.380	-0.422
	(0.317)	(0.310)
Industry size (sales share)		0.850
		(0.908)
Constant	0.134	0.089
	(0.163)	(0.175)
Obs	47	47
R^2	0.26	0.27

Table IA11: Inventory Physical Attributes and Exchange Trading

This table studies the relationship between physical attributes of commodities in inventory and the degree of exchange trading according to Rauch (1999). Columns (1) and (2) examine commodity-level data where we match commodities in Rauch (1999) with commodities in the BEA's 1997 input-output table following Nunn (2007): the outcome variable is an indicator variable that equals one if the commodity is exchange-traded, and the independent variables are design costs and transportation costs associated with each commodity. Columns (3) and (4) examine industry-level data: the outcome variable is the fraction of exchange-traded commodities in an industry's inventory (accounting for both raw materials and final goods), and the independent variables include industry-level inventory attributes (same as those in Table IA10). Each industry is a two-digit SIC. Column (1) and (3) use the conservative classification in Rauch (1999); columns (2) and (4) use the liberal classification. Robust standard errors are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

	Commodity Level		Industry Level	
	Conservative	Liberal	Conservative	Liberal
Design cost share	-1.757**	-2.964***	-2.521**	-6.250*
	(0.703)	(1.057)	(1.169)	(3.224)
Transportation cost	-0.025	-0.029	-0.111**	-0.249*
	(0.068)	(0.107)	(0.048)	(0.135)
Shelf life			0.056	0.092
			(0.057)	(0.162)
Constant	0.092***	0.160***	0.090**	0.234**
	(0.026)	(0.035)	(0.035)	(0.089)
Obs	342	342	42	42
R^2	0.03	0.05	0.17	0.15

IA5 Attributes and Liquidation Recovery Rates of Other Assets

In this appendix, we discuss the attributes that affect the liquidation recovery rates of other assets, such as receivables and book intangibles.

IA5.1 Receivables

Receivable liquidation recovery rates can be lower than 100% for several reasons. First, past-due receivables may not get paid in the end. Second, foreign receivables are difficult to recover. Third, government receivables and receivables against large, concentrated counterparties (e.g., Walmart) can also be difficult to recover. Fourth, some receivables can be offset by payables to the same counterparties and get netted out.

As before, we measure industry-level receivable attributes in 1997. For past-due receivables, we use the share of doubtful receivables in total receivables using Compustat. For foreign receivables, we calculate the share of non-US sales in total sales as a proxy, using Compustat segment data. For the possibility to offset receivables based on payables, we use accounts payables (normalized by book assets) as a proxy. We calculate the average value for each two-digit SIC.

Panel A of Table IA12 shows summary statistics of the receivable attributes. Panel B shows their relationship with the industry-average receivable liquidation recovery rate. As predicted, the receivable liquidation recovery rates are lower in industries with more doubtful receivables, foreign sales, and accounts payables. The impact of industry size (the industry's sales as a share of total sales in Compustat) is unclear like before, as shown in column (2).

Table IA12: Industry-Level Attributes of Receivables

Panel A shows the mean, standard deviation, and quartiles of industry-level receivable attributes. The attributes are calculated using Compustat data in 1997. Panel B shows the relationship between the industry-average receivable liquidation recovery rate and receivable attributes in the industry. Each industry is a two-digit SIC. Robust standard errors are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A. Summary Statistics

Variable	mean	p25	p50	p75	s.d.
Doubtful receivable share	0.077	0.050	0.062	0.081	0.054
Foreign sale share	0.101	0.039	0.108	0.165	0.131
Accounts payable	0.099	0.064	0.092	0.118	0.045
Industry size (sales share)	0.016	0.001	0.005	0.022	0.023

Panel B. Relationship with Receivable Liquidation Recovery Rate

	Receivable Liquidation Recovery Rate	
	(1)	(2)
Doubtful receivable share	-0.944**	-0.913**
	(0.354)	(0.364)
Foreign sale share	-0.174*	-0.176*
	(0.094)	(0.095)
Accounts payable	-0.957	-0.966
	(0.584)	(0.584)
Industry size (sales share)		0.594
		(0.723)
Constant	0.804***	0.791***
	(0.068)	(0.064)
Obs	47	47
R^2	0.14	0.15

IA5.2 Book Intangibles

For book intangibles, the liquidation recovery rate can be affected by the form and value of the intangibles. First, goodwill and organizational capital generate value when combined with the business as an operating enterprise, but do not have liquidation value. Intangibles that are separable and transferable can have liquidation values. Second, industry specialists comment that separable and transferable intangibles are mostly useful in the same industry and are more valuable in high margin industries.

We measure these attributes at the industry level in 1997, as before. We measure the industry-average share of goodwill in book intangibles in Compustat firms, as well as the industry-average share of knowledge capital in total intangible stock estimated by Peters and Taylor (2017) (which can proxy for the prevalence of transferable intangibles like patents and technologies relative to organizational capital). We also measure industry-average profit margin (net income divided by sales).

Panel A of Table IA13 shows summary statistics of these industry-level attributes. Panel B shows their relationship with the industry-average intangible recovery rate. As predicted, intangible liquidation recovery rates are lower in industries with more goodwill and higher in industries with more knowledge capital relative to organizational capital in the intangible stock. The relationship with industry size is unclear like before.

Table IA13: Industry-Level Attributes of Book Intangibles

Panel A shows the mean, standard deviation, and quartiles of industry-level intangible attributes. The attributes are calculated using Compustat data in 1997. Panel B shows the relationship between industry-average book intangible liquidation recovery rate and intangible attributes in the industry. Each industry is a two-digit SIC. Robust standard errors are presented in parentheses, and asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A. Summary Statistics

Variable	mean	p25	p50	p75	s.d.
Goodwill share in book intangibles	0.587	0.497	0.596	0.702	0.201
Knowledge capital share	0.082	0.004	0.039	0.116	0.118
Industry-average ROA	-0.009	-0.028	0.002	0.036	0.075
Industry size (sales share)	0.016	0.001	0.005	0.022	0.023

Panel B. Relationship with Book Intangible Liquidation Recovery Rate

	Book Intangible Liquidation Recovery Rate	
	(1)	(2)
Goodwill share in book intangibles	-0.442*	-0.483*
	(0.243)	(0.282)
Knowledge capital share	0.302	0.359
	(0.228)	(0.217)
Industry-average ROA	1.301	1.367
	(0.856)	(0.919)
Industry size (sales share)		-0.721
		(1.126)
Constant	0.424**	0.458**
	(0.185)	(0.220)
Obs	47	47
R^2	0.11	0.11

IA6 Additional Discussions

IA6.1 Prevalence of Operating Leases

In this appendix, we provide data about the prevalence of operating leases in different industries. Before 2019, the total amount of operating leases a firm has was not included in the balance sheet (only the annual lease expenses were reported). Since 2019, a new accounting rule (Accounting Standards Update 842) requires firms to report the value of leased (right-of-use) assets and corresponding operating lease liabilities on their balance sheets. We collect this data from Compustat and CapitalIQ. Based on this new disclosure, the median ratio of leased assets to owned assets is about 3.5% among Compustat firms; the inter-quartile range is 1.6% to 8.1%.[30] Moreover, the prevalence of operating leases also appears to be largely an industry attribute, and industry fixed effects (e.g., two-digit SIC) have an R^2 of about 40% for explaining the ratio of leased assets to owned assets across firms. Table IA14 shows the median ratio of operating lease to non-leased assets in each two-digit SIC code at the end of 2019. The ratio is particularly high for certain retail industries, modest for airlines and cinemas,[31] and low for most other industries. We also show the ratio or leased assets relative to owned PPE, which requires the additional assumption that leased assets are primarily PPE.

[30]Another way to estimate the prevalence of operating leases is to calculate assets owned by the two lessor industries in BEA data, which are 5320 (Rental and Leasing Services and Lessors of Intangible Assets) and 5310 (Real Estate, which includes REITs that lease real estate properties to others). The total (non-residential) assets owned by these two industries are also less than 5% of total assets owned by non-financial corporate businesses in the Flow of Funds. Since the lessor industries also include lessors to households (e.g., car rentals), this estimate would be upward biased.

[31]For instance, Southwest's 2019 Annual Report shows that it has 625 owned aircraft and 122 under operating leases, all of which are Boeing 737s. Similarly, United's 2019 Annual Report shows that it owns 635 out of 777 mainline (single-aisle and double-aisle) aircraft.

Table IA14: Prevalence of Operating Leases

This table shows the median ratio of operating lease relative to owned assets and relative to owned PPE in each two-digit SIC industry. The data comes from Compustat firms at the end of 2019.

SIC2	Operating Lease/Owned Asset	Operating Lease/Owned PPE
10 Metal Mining	0.000	0.000
12 Coal Mining	0.007	0.017
13 Oil/Gas Extraction	0.004	0.005
14 Quarrying-Nonmetals	0.015	0.039
15 Building Construction	0.000	0.000
17 Construction Contractors	0.017	0.105
20 Food Products	0.006	0.064
22 Textile Products	0.026	0.105
23 Apparel Products	0.133	1.333
24 Wood Products	0.028	0.180
25 Furniture and Fixtures	0.040	0.196
26 Paper Products	0.019	0.045
27 Printing and Publishing	0.055	0.394
28 Chemical Products	0.014	0.178
30 Rubber and Plastics Products	0.020	0.070
32 Stone, Clay, Glass, and Concrete	0.021	0.051
33 Primary Metal	0.012	0.025
34 Fabricated Metal Products	0.010	0.055
35 Machinery	0.018	0.127
36 Electronic Equipment	0.018	0.137
37 Transportation Equipment	0.010	0.040
38 Analytical Instruments	0.018	0.192
39 Misc. Manufacturing	0.022	0.171
41 Local Transit	0.054	1.167
42 Motor Freight	0.025	0.050
44 Water Transportation	0.028	0.041
45 Transportation by Air	0.105	0.200
47 Transportation Services	0.036	0.267
48 Communications	0.028	0.198
49 Electric and Gas	0.004	0.005
50 Wholesale Durables	0.025	0.219
51 Wholesale Non-Durables	0.022	0.081
52 Building Materials Dealers	0.126	0.276
53 General Merchandise Stores	0.180	0.531
54 Grocery Stores	0.138	0.275
55 Automotive Dealers	0.038	0.162
56 Apparel Stores	0.551	2.795
57 Furniture Stores	0.242	1.426
58 Restaurants	0.238	1.143
59 Misc. Retail	0.051	0.368
70 Lodging	0.007	0.022
72 Personal Services	0.025	0.119
73 Business Services	0.023	0.400
78 Motion Pictures	0.011	0.047
79 Amusement and Recreation	0.014	0.019
80 Health Services	0.044	0.413
82 Educational Services	0.015	0.068

IA6.2 Checks about Depreciation Rates

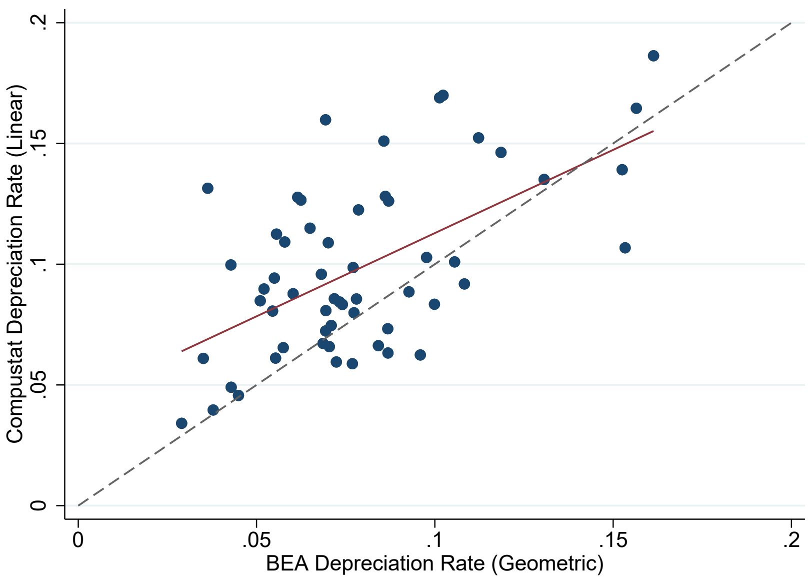
In the following, we check the reliability of depreciation rates used by firms. In particular, one concern is that if the depreciation rates firms use are too low, then the net book value will be overstated and the liquidation recovery rate (liquidation value/net book value) will be downward biased. To understand the depreciation rates firms use, we compare them with the depreciation rates used by the BEA.

For each firm in Compustat, we calculate its PPE depreciation rate using depreciation expenses relative to the stock of PPE. In addition, we calculate the fixed asset depreciation rate in its industry using the BEA fixed asset table. We find that depreciation rates used by firms are very similar to those used by the BEA. The correlation is about 0.6 and the average difference is about one percentage point. Figure IA8 shows an inudstry-level scatter plot of the depreciation rate used by Compustat firms (y-axis) and the BEA (x-axis).

Finally, we note that firms generally use linear depreciation whereas the BEA uses geometric depreciation. Given the similar depreciation rates, this implies that the net book value using firms' linear depreciation method tends to be smaller (which, if anything, would bias the liquidation recovery rate upward).

Figure IA8: Depreciation Rate Used by Compustat Firms and the BEA

This figure shows a scatter plot of the average depreciation rate based on Compustat firms (y-axis) and the BEA fixed asset table (x-axis). We calculate the depreciation rate in Compustat as the annual depreciation over lagged gross PPE (since Compustat firms generally use a linear depreciation method). We calculate the depreciation rate in BEA as the annual depreciation in each BEA industry over the lagged stock of fixed assets. We use data from 1996 to 2016 and plot the average value for each industry during this time period. The dashed line is the 45-degree line. The solid line is a fitted line.



IA7 Summary of Main Data Sources

The table below summarizes the main data sources used in our analyses, other than the liquidation recovery rate data.

Variable	**Source**
PPE mobility (transportation cost)	BEA Input-Output Table
PPE durability (depreciation rate)	Compustat
PPE customization (design cost)	BEA Input-Output Table
PPE composition	BEA Fixed Asset Table
Real GDP growth	FRED
Industry leverage	Compustat
Sale of PPE	Compustat
CAPX investment	Compustat
Inventory investment	Compustat
Firm-level return volatility	CRSP
Country-level macroeconomic volatility	World Bank
Intellectual property for BEA industries	BEA Fixed Asset Table
Firm-level intangibles	Compustat, Peters and Taylor (2017)
Large firm employment share	Census Statistics of US Businesses (SUSB)
Top 20 firm revenue share	Census
Vertical integration index	ORBIS, BEA Input-Output Table
Rule of law index	World Bank Development Indicators

In addition, we use two-digit SICs as the baseline industry categorization whenever possible (since the liquidation recovery rate data uses SIC codes). However, when the outcome variable is measured using another industry categorization, then we perform analyses using the corresponding industry classification (which requires matching the liquidation recovery rate data into these alternative industry codes). For instance, the outcome variables come with ISIC industries in Table 6, four-digit NAICS in Table 8, and four-digit BEA input-output table industry in Table 9.