Asset Specificity of Non-Financial Firms*

Amir Kermani[1] and Yueran Ma[2]

[1]Berkeley Haas
[2]Chicago Booth

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Abstract

The specificity of firms' assets affects a wide range of issues in macroeconomics and finance. We study asset specificity of U.S. non-financial firms using a new dataset on the liquidation recovery rates of all major asset categories across industries. First, we find that non-financial firms' assets are generally highly specific. The average recovery rate (liquidation value over cost net of depreciation) is 33% for plant, property, and equipment (PPE). Second, across industries, physical attributes such as mobility, durability, and standardization account for around 40% of variations in PPE recovery rates. Over time, macro conditions have the most impact on recovery rates when PPE is neither industry-specific nor firm-specific, while industry conditions have the most impact when PPE is industry-specific but not firm-specific. Third, higher asset specificity is associated with less asset sales, greater investment response to uncertainty, and more Q dispersion, consistent with theories of investment irreversibility. Finally, the data suggests that rising intangibles have had a relatively limited impact on firms' liquidation values.

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Emails: kermani@berkeley.edu, yueran.ma@chicagobooth.edu.

1 Introduction

Asset specificity is a key feature of production activities in practice. As Bertola and Caballero (1994) articulate, once installed, capital often has "little or no value unless used in production." Asset specificity also plays a prominent role in a wide range of economics research. It can lead to investment irreversibility (Pindyck, 1991; Bertola and Caballero, 1994; Abel and Eberly, 1996), and influence price setting (Woodford, 2005; Altig, Christiano, Eichenbaum, and Linde, 2011). It may also affect the form of organizations (Williamson, 1981), as well as debt contracting (Shleifer and Vishny, 1992; Kiyotaki and Moore, 1997).

The central challenge for studying assets specificity and its implications is measurement. What is the value of different assets if they were displaced, separated from current use and moved to alternative use? Such data has been sparse so far, and secondary market trading information is only readily available for a limited and selected subset of assets. An important prior work is Ramey and Shapiro (2001), which collects comprehensive data from auctions of aerospace manufacturing equipment, and estimates that the transaction value of equipment is on average 28% of replacement cost. Other studies generally rely on imputations or indirect proxies such as the prevalence of asset usage across industries (Berger, Ofek, and Swary, 1996; Almeida and Campello, 2007; Gulen and Ion, 2016; Kim and Kung, 2017). With the lack of systematic data on the degree of asset specificity, models have also used a wide range of parameter values.

In this paper, we tackle the challenge by constructing a new dataset that directly measures asset specificity for all major asset types (e.g., fixed assets, inventory, receivables, etc.) and major industries. We document that assets are highly specific in most industries. We then investigate the key determinants of variations in asset specificity, including physical attributes of assets used in different industries (such as mobility, durability, standardization/customization), as well as macroeconomic and industry conditions. We finally show the implications for several issues in macro-finance, including predictions of investment theories as well as the impact of rising intangibles.

To fix ideas, for each type of asset, we quantify the degree of asset specificity using the resale value in liquidation relative to the replacement cost, henceforth referred to as the liquidation recovery rate. This ratio corresponds to the degree of investment irreversibility in a number of models (Abel and Eberly, 1996; Bloom, 2009). Alternatively, one might also think of asset specificity defined as the ratio of the value in alternative use relative to the value in current use. The value in current use is unfortunately difficult to assess for each individual asset category (since a firm has multiple types of assets and one can only observe the market value of the firm as a whole). To the extent that the value in current use is typically higher than the replacement cost, this alternative ratio would generally imply an even higher degree of asset specificity.

The first step of our work is to collect data on the liquidation recovery rates of major types of assets across industries. The most systematic reporting of this information comes from the liquidation analysis in Chapter 11 bankruptcy filings, and we hand collect this data from 2000 to 2016. Specifically, firms in Chapter 11 continue to operate, but are also required to document the estimated value of their assets if they were to be liquidated in Chapter 7—in which case the firm would cease operations and a trustee liquidates its assets. These estimates commonly derive from specialist appraisers who perform on-site field exams and simulate live liquidations.[1] The large cases typically report in detail the estimated liquidation recovery rate for each category of asset, such as plant, property, and equipment (PPE), inventory, receivables, cash, book intangibles, among others. We take the average recovery rate for each type of asset in a 2-digit SIC industry in the baseline analysis to reduce noise, which currently covers nearly 50 non-financial 2-digit SIC industries.

We find that firms' assets are highly specific on average, but there are meaningful variations across industries. The industry-level liquidation recovery rate for PPE is 33% on average, and it ranges from close to 70% for transportation to less than 10% for certain services. The industry-level liquidation recovery rate for inventory is 44% on average, and it ranges from about 80% for auto dealers and retailers to less than 20% for restaurants. If we take the industry-level liquidation recovery rate and estimate the total liquidation value of firms in Compustat based on their industries and the book value of each type of asset, we find that the total liquidation value of PPE and working capital combined is 23% of total book assets for the average firm (and 45% when other assets and all of cash are also included). In addition to the comparison with book values, at the firm level, the estimated total liquidation value (including all assets and cash) is about 50% of the enterprise value for the median firm in the Chapter 11 sample, and 33% in Compustat. Overall, non-financial firms' assets are specialized and the piecemeal value to alternative users tends to be low, relative to both replacement costs and firm values from current use.

We perform extensive checks for the informativeness of the data. They verify that the liquidation value estimates in our data are consistent with market-based transactions (in settings where such data is available). They also verify that the degree of asset specificity is not somehow very different for firms in Chapter 11. First, for aerospace manufacturing equipment that Ramey and Shapiro (2001) study using auctions data, the recovery rate is 28% in their analysis and 32% in our sample. Second, the total liquidation value in

[1] The appraisal firms have knowledge, experience, and historical data on what would be a feasible way to conduct a liquidation: how much can be sold to buyers from primary, secondary, and tertiary markets, and at what price, etc. These firms commonly serve as liquidators as well. They also provide liquidation value estimates for lenders who lend on the basis of the liquidation value of discrete assets.

our data is comparable to the total liquidation proceeds in actual Chapter 7 liquidations (unfortunately Chapter 7 cases offer much less information beyond the total proceeds realized by the trustee).[2] Third, the liquidation recovery rates in our data are also in line with lenders' benchmarks for non-financial firms, which are 20% to 30% for industrial PPE for instance according to a large bank. Fourth, we compute the industry-average recovery rates implied by PPE sales among all Compustat firms, and find them to be similar in level to PPE liquidation recovery rates in our data, with a significant positive correlation between the two measures across industries. Finally, the informativeness of the data is further reflected by its consistency with the physical attributes of assets used in different industries (measured for all firms in each industry from separate data sources), and with the investment behavior of firms overall, which we analyze in the rest of the paper.

The second step of our work is to examine the key determinants of variations in asset specificity, using PPE liquidation recovery rates as the main example. We begin by studying the impact of three physical attributes: 1) mobility, measured using the transportation costs of PPE; 2) durability, measured using the depreciation rate of PPE, since asset reallocation takes time; and 3) degree of standardization/customization, measured using the average share of design costs in the production costs of PPE. To construct these measures, we collect detailed information on the composition of each industry's asset stock using the fixed asset tables from the Bureau of Economic Analysis (BEA), as well as transportation costs and design costs using the BEA's input-output tables. We show that asset specificity is higher and liquidation recovery rates are lower when the asset is less mobile, less durable, and more customized. Indeed, these three attributes can account for around 40% of the variations in the average PPE recovery rate across industries, despite potential measurement noise. Moreover, the estimates also imply that if PPE has no transportation cost, no depreciation, and no customization, the recovery rate would be 100%. Overall, the findings indicate strong physical foundations for variations in asset specificity.

We also study the impact of time-varying macroeconomic conditions and industry conditions. We find that the average relationship is in the direction of theoretical predictions, but somewhat weak. However, macro conditions have a particularly strong impact on PPE recovery rates for industries with a large share of PPE that is neither industry-specific nor firm-specific (e.g., vehicles). Industry conditions have a particularly strong impact for industries with a large share of PPE that is industry-specific but not firm-specific (e.g., aircraft, ships, railroad equipment, oil and gas equipment). In other words, when natural buyers are economy-wide (i.e., assets are neither firm-specific nor industry-specific), macro conditions

[2] In Chapter 7 cases, it is difficult to calculate the liquidation recovery rate for each type of asset. Assets foreclosed by lenders or abandoned by the trustee are also generally excluded from the reported total proceeds, which requires additional imputation (Bris, Welch, and Zhu, 2006).

are particularly relevant. When natural buyers are concentrated within the industry (i.e., assets are not firm-specific but industry-specific), industry conditions are particularly relevant. When there are no natural buyers of PPE on a standalone basis to begin with (i.e., assets are customized to the firm), macro conditions and industry conditions appear less relevant. We also find that the cross-industry differences in PPE recovery rates (driven by physical attributes) seem generally larger than the impact of cyclical variations. For example, to bring PPE recovery rate from the highest industries (e.g., transportation) to the median (e.g., typical manufacturing), industry conditions such as industry leverage would need to change from 0 to roughly 140%.

After analyzing the determinants of asset specificity, the third step of our work is to investigate the implications of asset specificity for firms' behavior. We start with traditional investment theories. As observed by a large literature, when asset specificity is higher, it is more difficult to disinvest and downsize the capital stock: investment is more irreversible (Pindyck, 1991; Bertola and Caballero, 1994; Abel and Eberly, 1996; Bloom, 2009, 2014). We first verify that in industries with lower PPE recovery rates, firms have less PPE sales, in terms of both frequencies and dollar amounts. We then show that, as predicted by theory, capital expenditures (i.e., spending on PPE) are more sensitive to uncertainty shocks when PPE recovery rates are lower. Indeed, the sensitivity is estimated to be zero if the PPE recovery rate is 100%. We also find that inventory investment is more sensitive to uncertainty shocks when inventory recovery rates are lower, and the estimated sensitivity is again zero if the inventory recovery rate is 100%. Furthermore, the sensitivity of PPE investment to uncertainty is affected by PPE recovery rates but not by inventory recovery rates, and vice versa. Our results hold based on direct measurement of recovery rates, as well as recovery rates "instrumented" (or "fitted") using the assets' physical attributes.

We also find evidence in line with several other implications of costly capital adjustment and irreversibility. First, for pricing behavior, we find that industries with higher asset specificity display more price rigidity, based on price change data from Nakamura and Steinsson (2008). The results appear consistent with the literature on firm-specific capital and price stickiness (Woodford, 2005; Altig et al., 2011). Second, for productivity dispersion, we find that industries with higher asset specificity display more dispersion in Q, in line with the observations of Eisfeldt and Rampini (2006) and Lanteri (2018). This phenomenon holds for large firms as well, where liquidation values are not a primary driver of financial frictions like borrowing constraints (Lian and Ma, 2020), which suggests that asset specificity likely has its impact through costly adjustment.

In addition to implications for traditional investment theories, we also study implications of our data for understanding the impact of rising intangible assets (Corrado, Hulten, and

Sichel, 2009; Peters and Taylor, 2017), broadly defined as production assets without physical presence. They include identifiable intangibles such as software, patents, usage rights, as well as organizational capital that is not necessarily independently identifiable. A common concern is that rising intangibles could decrease firms' liquidation values, and then tighten borrowing constraints (Giglio and Severo, 2012; Caggese and Perez-Orive, 2018; Li, 2019; Falato, Kadyrzhanova, Sim, and Steri, 2020). We find that the change in firms' liquidation values in recent years may not be substantial, for three reasons. First, as discussed above, physical assets are highly specific to begin with. Second, in many industries, the average liquidation recovery rates of identifiable intangibles do not appear to be much lower than those of PPE, in part because reallocating intangibles does not face transportation costs given their lack of physical presence. Third, industries with a greater increase in intangibles have been the ones with more specific physical assets in the first place. Taken together, the aggregate liquidation value among Compustat firms in 2016 is similar to that in 1996.

It would be natural to ask how asset specificity affects firms' debt contracts and borrowing capacity, which we study in detail in a companion paper (Kermani and Ma, 2020). We find that liquidation values do not affect the total amount of borrowing for large firms and firms with positive earnings. They do have a significant positive impact on total borrowing for small firms and firms with negative earnings. Meanwhile, asset specificity does affect the composition of debt: firms with higher liquidation values have more asset-based debt (lending on the basis of the liquidation value of discrete assets like PPE), while firms with lower liquidation values have more cash-flow based debt (lending on the basis of cash flows from firms' operations) and debt with strong control rights. The results are consistent with observations in Lian and Ma (2020) about the importance of cash-flow based lending among non-financial firms. When firms have positive earnings (e.g., most large firms), total debt capacity is typically driven by earnings-based borrowing constraints, instead of the liquidation value of discrete assets.

Finally, we connect our data with parameters in models, which have used or estimated a variety of values for the degree of investment irreversibility or the amount of liquidation value from physical capital. We hope that our micro data helps inform modeling analyses.

Our work has three main contributions. First, we provide comprehensive data on the degree of asset specificity across different types of assets and industries. Second, we investigate the impact of physical attributes, as well as macro and industry conditions, on variations in asset specificity. Third, the granular and quantitative nature of our data allows us to perform a rich set of analyses about the implications of asset specificity. Our findings shed light on the impact of investment irreversibility and rising intangibles. The physical attributes of assets we measure also allow us to establish these links based on physical foundations.

The paper is organized as follows. Section 2 explains the data collection and presents basic statistics. Section 3 studies the determinants of asset specificity, including physical attributes as well as macro and industry conditions. Section 4 investigates several implications. Section 5 summarizes the comparison with parameters in models. Section 6 concludes.

2 Data and Basic Statistics

In this section, we discuss the data and measurement of asset specificity. We collect data on liquidation recovery rates—i.e., liquidation value as a fraction of net book value (cost net of depreciation)—of major asset categories (e.g., PPE, inventory, receivable, book intangibles) across major industries. The liquidation value estimates represent proceeds from a typical orderly liquidation process, and provide information about the value of each type of asset in alternative use. By definition, high asset specificity means limited value in alternative use, and correspondingly a low liquidation recovery rate.

We normalize the liquidation value using replacement costs, similar to Ramey and Shapiro (2001). An alternative approach is to normalize the liquidation value using the value of the asset in current use. Our approach is driven by three main reasons. First, data on the net book value is available for each type of asset, while the value in current use is difficult to assess for a particular category of assets. Second, the liquidation value relative to costs is commonly used in models, which we discuss in more detail in Section 5. Third, the ratio of the liquidation value relative to costs is, to a large extent, determined by the inherent attributes of assets used in a given industry (as we further verify in Section 3), and can be more reliably generalized to firms in the same industry. The ratio of the liquidation value relative to the value in current use, on the other hand, could depend on managerial quality that affects the denominator. Nonetheless, for the firm as a whole, we can still provide some information of the ratio of the total liquidation value relative to the firm's enterprise value, which we discuss in Section 2.4.

2.1 Data Collection

To systematically measure the degree of asset specificity of non-financial firms, secondary market transactions data faces a number of challenges. First, such data is available for certain types of relatively standardized assets (e.g., vehicles, aircraft, construction equipment), but difficult to obtain for many types of real assets. Second, it is also difficult to know the pool of assets firms own, in which case one cannot aggregate individual items to an estimate at the firm level. To overcome these obstacles, a setting with comprehensive reporting covering all assets firms own is the liquidation analysis performed in Chapter 11 corporate reorganization. When firms complete Chapter 11, they need to document the estimated liquidation value that their assets can obtain if they were to be liquidated in Chapter 7, where the firm ceases operations and a trustee liquidates its assets (largely piecemeal with a roughly one year time frame). The estimates generally derive from appraisal specialist firms, who usually serve as liquidators of real assets as well. They perform field exams and simulate live liquidations to appraise the liquidation value of different types of assets. They are also commonly responsible for assessing liquidation values for lenders who lend against particular assets and set borrowing limits accordingly, which follows a similar appraisal process.

We hand collect liquidation recovery rate data from disclosure statements of Chapter 11 filings, for US non-financial firms from 2000 to 2016. Specifically, we begin with a list of bankruptcy filings by public US non-financial firms from New Generation Research BankruptcyData.Com. We then retrieve the disclosure statements of Chapter 11 cases from Public Access to Court Electronic Records (PACER) and BankruptcyData.Com.[3] 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 entity as a whole, together with notes that explain in more detail the sources and assumptions of the estimates. Figure 1 below 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 facility-level appraisals for Lyondell's PPE. We use the midpoint estimate in the summary table, and the average of low and high scenarios when the midpoint is not available. We have been able to retrieve liquidation analysis summary tables for 360 cases so far, covering 48 2-digit SICs.

This data has several advantages. First, as mentioned above, it covers *all assets* owned by a firm, instead of only assets with secondary market trading data (which tend to exclude specialized assets) or are chosen to be sold off, which may entail selection (Ramey and Shapiro, 2001; Maksimovic and Phillips, 2001). Second, it shows not just the liquidation value in dollar amounts, but also the recovery rate, i.e., liquidation value as a fraction of book value. Having recovery rates is important for comparing specificity across different types of assets, and for constructing specificity measures more broadly for each industry as we discuss below. Third, the data includes firms from all major industries in a reasonably standardized format. Finally, relative to indirect proxies of asset specificity, our data allows for the assessment of the dollar magnitude (important in many applications such as issues analyzed in Section 4), provides a uniform metric across different types of assets (e.g., PPE

[3] 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.

and inventory), and connects directly to model parameters (discussed in Section 5).

Our data covers assets owned by firms. Some assets that firms use may be under operating lease, instead of being owned. The owned assets within the boundary of the firm are our primary focus for several reasons. First, real decisions like investment expenditures capture spending on owned assets. Second, owned assets appear to dominate in quantity. Specifically, prior to 2019, firms' financial statements only report owned assets; starting in 2019, a new accounting rule (Accounting Standards Update 842) requires firms to also report leased (right-of-use) assets and corresponding operating lease liabilities. Based on the new disclosure, the median ratio of leased assets to owned assets is about 2% among Compustat firms (the inter-quartile range is 0% to 5.5%).[4] Finally, the prevalence of operating leases appears to be primarily an exogenous industry attribute; firm-specific characteristics have much less explanatory power in comparison. In particular, industry fixed effects (e.g., 2-digit SIC) account for about 40% of R^2 in the variation of the ratio of leased assets to owned assets, while basic firm characteristics account for less than 1%. The ratio of leased to owned assets is particularly high for certain retail industries (median above 20% for restaurants, department stores, apparel, furniture, hardware, and food stores), modest for airlines and cinemas (median around 10%), and very low (median well below 10%) for most other industries.

2.2 Checks of Data Informativeness

We perform extensive checks to examine the reliability of the data. They verify that the liquidation value estimates in our data are consistent with market-based outcomes (in settings where such data is available), such as liquidation proceeds in Chapter 7 and auction proceeds. They also show that the degree of asset specificity does not appear to be much different for firms in Chapter 11. As we analyze in detail in Section 3, the degree of asset specificity is substantially driven by the physical attributes of assets an industry's production process requires, which apply to all firms in the industry.

First, in Kermani and Ma (2020), we perform a detailed comparison between total liquidation value estimates from Chapter 11 filings and actual liquidation values in Chapter 7 cases. Chapter 7 cases only produce a Trustee's Final Report with total liquidation proceeds, but not liquidation recovery rates for each asset type, so the information is more limited.[5]

[4] Another way to estimate the prevalence of operating leases is to calculate assets owned by the two lessor sectors 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 sectors are also less than 5% of total assets owned by non-financial corporate businesses in the Flow of Funds. Since the lessor sectors also include some lessors to households (e.g., car rentals), this estimate would be upward biased.

[5] 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

For firms in the same industry, we find the estimated total liquidation values (normalized by total assets at filing) in Chapter 11 liquidation analyses are similar to total proceeds in Chapter 7 liquidations.

Second, we cross check with other studies using data from liquidation auctions. Specifically, Ramey and Shapiro (2001) analyze equipment liquidations of three large aerospace manufacturing plants in California. Ramey and Shapiro (2001) estimate that the equipment liquidation recovery rate is around 28%. In our data, based on the same 3-digit SIC (SIC 372), the liquidation recovery rate on machinery and equipment is 32%, which is very close.

Third, as explained in detail in Kermani and Ma (2020), the average liquidation recovery rates in our data also line up with benchmarks and debt limits lenders use when they lend against the liquidation value of particular assets such as PPE, inventory, and receivable.

Fourth, we also estimate the recovery rates implied by PPE sales among Compustat firms. Specifically, firms' financial statements report proceeds from sales of PPE (Compustat variable SPPE). For each firm-year with positive PPE sales, we can construct the net book value of PPE sold (i.e., lagged net PPE + capital expenditures − depreciation − current net PPE). We exclude firm-years with positive acquisition spending as it is difficult to tease out PPE changes due to acquisitions. We construct the PPE sale recovery rate as PPE sale proceeds normalized by the net book value of PPE sold. We calculate the average PPE sale recovery rate in each 2-digit SIC industry over our sample period (2000 to 2016), and compare it to the industry-average PPE liquidation recovery rate in our data. We find the difference is small: the average (median) difference is 0.036 (0.025), and the inter-quartile range is -0.07 to 0.11. In addition, Internet Appendix Figure IA1 shows that the liquidation recovery rates and the sale recovery rates are fairly correlated. The raw correlation is 0.36, significant at the 1% level. The limitation of PPE sale recovery rates is that they only capture a subset of PPE, and only one type of asset, so we focus on the liquidation recovery rate data for our main analyses.

We can also further investigate whether the liquidation recovery rates or the sale recovery rates are affected by firm characteristics within an industry, which we analyze in Internet Appendix Table IA1. We find that the recovery rates of PPE have a positive association with firms' operating earnings (EBITDA). In terms of economic magnitude, if profitability (EBITDA normalized by book assets) changes by ten percentage points, the recovery rates would change by around one percentage point. This sensitivity is small, given that the inter-quartile range of profitability among Compustat firms is less than 25 percentage points (from -0.08 to 0.16). We do not find a significant relationship between recovery rates and book

realized by the trustee, which can create complications. We follow Bris et al. (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.

leverage. In sum, asset specificity and resale values appear to be predominantly driven by features of the industry (which we investigate more in Section 3), and less by the conditions of a given firm.

Finally, in Section 3 below, we demonstrate that variations of liquidation recovery rates across industries are closely connected to the physical attributes of assets different industries use, measured among all firms in each industry using separate data sources. In Section 4, we show that the liquidation recovery rates in our data explain an important set of firm outcomes, among Compustat firms in general. Taken together, while we have the most comprehensive data from the Chapter 11 sample, it reflects general features of assets used by firms in the same industry and contains valuable information.

2.3 Asset-Level Recovery Rates

We construct the measure of asset specificity, for each type of asset in an industry, by calculating the average liquidation recovery rates among all Chapter 11 cases. The main asset categories include PPE, inventory, receivables, and book intangibles, among others, which correspond to the standard asset categories in financial statements. Each industry is a 2-digit SIC code. Averaging by industry has two functions. First, it can reduce idiosyncratic noise at the individual case level. Second, as mentioned above, asset specificity is to a large extent an industry attribute, driven by the nature of production activities in different industries (e.g., physical attributes of assets used by different industries). These industry-level measures can be extended to firms in an industry more broadly.

Table 1 provides a summary of the industry-level liquidation recovery rates of PPE, inventory, and receivable. For PPE, the average industry-level liquidation recovery rate is 33%, i.e., the liquidation value of PPE is on average 33% of net book value (cost net of depreciation). This number is reasonably low, indicating that PPE is often specialized and the value in alternative use can be limited. Some industries, however, have more generic PPE, such as transportation (average liquidation recovery rate for PPE around 70%). For inventory, the average industry-level liquidation recovery rate is 44%. It is very high for industries such as auto dealers (close to 90%), as well as retailers like apparel stores and supermarkets (around 75%), given the generic nature of their inventory. It is very low for restaurants (around 15%), since their inventory primarily consists of fresh food which is highly perishable. For receivables, the average industry-level liquidation recovery rate is 63%. Receivables may not have full liquidation recovery rates because of foreign receivables, government receivables, and receivables from concentrated large customers, which are difficult to enforce. Some receivables may also be offset by payables to the same counterparties.

2.4 Firm-Level Liquidation Values

We can also combine the liquidation value of different types of assets, and construct the estimated firm-level liquidation value $Liq_{i,t} = \sum_j \lambda_{i,j} K_{i,j,t}$, where $Liq_{i,t}$ is the total liquidation value of firm i at time t from different types of assets, j denotes the asset type (e.g., PPE, inventory), $\lambda_{i,j}$ is the liquidation recovery rate of this type of asset based on the firm's industry (as explained above in Section 2.3), and $K_{i,j,t}$ is the book value of asset j for firm i at time t. The baseline sample period for Compustat firms is 1996 to 2016.

The firm-level liquidation value estimate relies on the assumption that the attributes of assets within an industry are broadly similar (e.g., steal mills use similar equipment). While there can be variations across firms in an industry based on their location, equipment vintage, etc. (as is well-ackowledged by appraisal specialists), we need some industry-level aggregation of recovery rates to make the data more widely applicable. As discussed above, there is substantial consistency within an industry and substantial information in the industry-average recovery rate. In Section 3, we show that variations in industry-average recovery rates are closely linked to the physical attributes of assets used in each industry. In Section 4, we show that these variations also have significant explanatory power for firms' investment behavior in each industry.

Table 2, Panel A, shows summary statistics of firm-level liquidation values (normalized by total book assets) estimated for Compustat firms. We include PPE and working capital (inventory and receivable) in the baseline variable. The mean and median are about 23%; the inter-quartile range is 12% to 33%. We can additionally include cash holdings. In this case, the mean and median are around 43%; the inter-quartile range is 30% to 54%. Table 2, Panel B, shows other basic statistics of firms in the sample. Internet Appendix Figure IA2, Panel A, shows the distribution of firm-level liquidation values. Figure IA2, Panel B, shows the liquidation value composition for the average Compustat firm.

As explained at the beginning of this section, our main analysis compares liquidation values to replacement costs (book values) of each type of asset. Nevertheless, for the firm as a whole, we can also compare the total liquidation value (from all types of assets) with the enterprise value of the firm. This comparison sheds light on the piecemeal liquidation value of a firm (the "intrinsic" value of standalone assets if the firm is "dead") relative to its going-concern value (the present value of cash flows from the firm's continuing operations if it is "alive"). For firms in the Chapter 11 sample, we can directly observe assessment of their total liquidation value and going-concern value (we use post-emergence firm market value data for those firms that emerged as public firms, and estimated going-concern value in the Chapter 11 confirmation plan otherwise). The median ratio is 50% (inter-quartile range 32% to 74%). For Compustat firms, we compare the estimated liquidation value $Liq_{i,t}$ including all major types of assets (PPE, working capital, as well as cash and book intangibles), with their market values. The median ratio is 33% (inter-quartile range 20% to 51%). 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.

Overall, we find that liquidation values are fairly limited for many firms. Their assets, if redeployed for alternative use on a standalone basis, have limited value. This applies not only to the traditional stereotypes of technology or health care industries, but represents a more general phenomenon for many firms in manufacturing and services.

3 Determinants of Asset Specificity

In this section, we analyze the determinants of asset specificity. In particular, we investigate what explains the variations in liquidation recovery rates across industries and over time. In Section 3.1, we analyze the role of physical attributes of the assets used in different industries. In Section 3.2, we study the impact of time-varying macroeconomic conditions and industry conditions. Below we focus on PPE. We examine the determinants of the specificity of inventory and other assets in the Internet Appendix Sections IA4 and IA5.

3.1 Physical Attributes

We analyze three key physical attributes that affect the specificity of PPE. The first attribute is mobility: some assets are very mobile (e.g., aircraft, ships, vehicles), which helps them reach alternative users more easily, while other assets are location-specific (e.g., buildings) or difficult to transport (e.g., nuclear fuel). The second attribute is durability: reallocation takes time and assets that depreciate faster can be less valuable by the time they are delivered to alternative users (fresh food being an extreme example). The third attribute is the degree of standardization or customization: some assets are standardized or can be relatively readily used by any firm that needs such assets (e.g., railroad cars, trucks), while other assets are customized for a particular user (e.g., eyeglasses for individuals or optical lenses for industrial production). These three attributes all affect the distribution of the productivity of the asset 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, the amount of alternative users with high valuation of the asset decreases, and the equilibrium liquidation value is lower.

In Section 3.1.1, we explain the measurement of these physical attributes of PPE across industries. We primarily use information on the composition and attributes of fixed assets in each industry based on data from the Bureau of Economic Analysis (BEA). In Section 3.1.2, we show that the physical attributes of assets in each industry have substantial explanatory power for the variation in asset specificity across industries.

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 (39 types of equipment and 32 types of buildings and structures) across 58 BEA industries. We denote the fixed asset stock as K_{ij}, where i is a BEA industry and j is one type fixed asset. The 71 types of equipment and structures are listed in Internet Appendix Table IA3. Using this granular information, we can analyze the physical attributes of each type of fixed asset (j), and assess the overall characteristics of PPE in an industry (i) using the fixed asset composition (the share of K_{ij} in $K_i = \sum_j K_{ij}$). 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. We explain the details of the measurement below.

Mobility

We measure the mobility m_j for each type of PPE using the ratio of transportation costs (from its producers to its users) relative to production costs. For each of the 71 fixed assets, we obtain this ratio using BEA's input-output table (we link assets in the fixed asset table with output in the input-output table using BEA's PEQ bridge). For equipment, this data is generally available. For fixed structures like buildings, this data may not be available, in which case we estimate the ratio to be one (i.e., buildings are completely immobile). Among non-structures, assets with the lowest transportation costs (highest mobility) include storage devices and computer terminals, 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 2-digit SICs, which are the industry codes in our Chapter 11 liquidation analysis data. Table IA4 in the Internet Appendix lists the 58 industries in the BEA fixed asset table, and the corresponding 2-digit SIC industries. Industries with the highest overall PPE mobility (lowest transportation costs for overall PPE) include water transportation and air transportation. Industries with the lowest overall PPE mobility (highest transportation costs for overall PPE) include educational services, hotels, and pipelines.

Durability

We measure the durability using depreciation rates. The simplest approach is to calculate the average depreciation rate of PPE (depreciation divided by lagged net PPE) in each 2-digit SIC industry using Compustat data, which avoids translating BEA industries to SIC. Alternatively, we can also calculate the depreciation rate for each industry in the BEA fixed asset table, and match it to 2-digit SIC industries. This approach produces qualitatively similar results, but can be noisier due to industry matching. Fixed assets with the highest durability (lowest depreciation rate) include electricity structures and sewage systems. Fixed assets with the lowest durability (highest depreciation rate) include computers and office equipment. Industries with the highest overall PPE durability (lowest overall PPE depreciation rate) include railroad transportation, fishing, and utilities. 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 required more design and related input in the production of such assets, while standardized assets can be directly produced. For each of the 71 fixed assets, we calculate this share using BEA's input-output table (i.e., we look at what it takes to produce each type of PPE).[6] Nonetheless, an imperfection in this measure is that some standardized assets may also be relatively design-intensive, such as aircraft, which can make the measure noisy and may work against us. 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 does not include the cost of design, R&D, etc.—in total operating cost in the production of an asset, which produces similar results. Input assets with the lowest degree of customization include mobile structures, trucks/cars, mining equipment, and nuclear fuel. Input assets with the highest degree of customization include communication structures, fabricated metals, and special industrial machinery.

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

[6] In the BEA input-output table, we calculate design and related costs as input costs from the following categories: design, information services, data processing services, custom computer programming services, software, database, other computer related services, architectural and engineering services, research, management consulting, advertising.

customization measure is the share of design costs in total production costs of all PPE in each industry. We match BEA industries with 2-digit SICs. Industries with the lowest overall degree of PPE customization include transportation industries. Industries with the highest overall degree of PPE customization include communications industries.

Other Attributes

Kim and Kung (2017) use another attribute to proxy for asset redeployability, which measures the number of industries that use a certain type of asset. So far we do not find that measures following Kim and Kung (2017) help to explain variation in PPE liquidation recovery rates in our data. Some of the most mobile, durable, and standardized assets are used primarily in a few industries (e.g., ships and railroad equipment). Meanwhile, many assets used in a large number of industries are relatively costly to move, not durable, or customized (e.g., furniture, computers and office equipment, and optical lenses). These issues can weaken the relationship between asset redeployability and how widely an asset is used across industries.

Relatedly, within the airline industry, Gavazza (2011) finds that aircraft types with larger outstanding stock, and therefore "thicker" markets, have higher sale prices. Using 19th century railroads, Benmelech (2008) proxies for asset redeployability using the size of railroads with a particular gauge. In our data, we do not find that the amount of fixed asset stock is linked to PPE liquidation recovery rates. There are several possibly important differences between our setting and the settings of Gavazza (2011) and Benmelech (2008). First, for aircraft of different types or railroads of different gauges, the other attributes (mobility, durability, and customization) are fairly homogeneous. In comparison, for different types of PPE across industries, these other attributes have substantial variations, which can be first-order. Second, a given type of aircraft is reasonably well defined (Boeing 737-700/800/900 etc.), and railroads with a given gauge are also well defined. On the other hand, the categorization of assets in the BEA fixed asset table is looser. For instance, in the BEA fixed asset table, the asset type with the largest stock is manufacturing structures. If BEA alternatively breaks down manufacturing structures by industry (e.g., chemical plants vs. steel plants), then the stock for each type of manufacturing structure would be smaller. Overall, in our data, the size of the stock of a particular type of asset may not be an ideal measure, given the asset categorization in the BEA fixed asset table (there can be further subdivisions or customization within a BEA category).

In summary, we use mobility, durability, and customization as the primary measures of physical attributes. Our baseline analysis relies on the 1997 input-output table. The BEA produces input-output accounts and several capital accounts every five years, and 1997 has the most comprehensive information. 1997 is also around the beginning of our liquidation recovery rate data. Correspondingly, we use all other data input for physical attributes (e.g., the BEA fixed asset table, depreciation rates, industry codes) from 1997. Internet Appendix Table IA5 shows the industry-level summary statistics for 2-digit SIC industries.

3.1.2 Explanatory Power of Physical Attributes

In Table 3, Panel A, we study the relationship between industry-level PPE liquidation recovery rates and the physical attributes of PPE in each industry. Columns (1) and (2) use 2-digit SIC industries. Columns (3) and (4) use BEA sectors. We find that physical attributes have substantial explanatory power for the variation in PPE liquidation recovery rates across industries. Industries where PPE has high transportation cost, high depreciation rate, and high customization have low PPE liquidation recovery rates. The effect is both statistically and economically significant. A one standard deviation change in mobility (transportation cost), durability (depreciation rate), and standardization (design cost) is associated with changes in PPE recovery rate of 0.59, 0.35, and 0.27 standard deviations respectively, based on column (1). In addition, the constant in the regression is about one, indicating that when transportation costs, depreciation, and design costs are all zero (PPE is costless to transport, non-depreciating, and fully standardized), the recovery rate is estimated to be 100%. Finally, the R^2 is close to 40%: at least 40% of the variation in PPE liquidation recovery rates can be explained by proxies of the physical attributes. Given that the proxies of physical attributes may be imperfect, and the matching between BEA sectors and SICs can also be imperfect (e.g., BEA groups all retail industries into one industry, while there are eight 2-digit SIC retail industries), the true explanatory power of physical attributes could be even higher.

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

Taken together, a central part of the variations in the specificity of fixed assets is linked to their physical attributes, given by the nature of the industry. The physical attributes of PPE in an industry, measured using independent data sources, have a strong explanatory power for PPE recovery rates in the liquidation analysis data.

3.2 Macroeconomic and Industry Conditions

Next we examine how macroeconomic and industry conditions affect PPE liquidation recovery rates on top of their physical attributes. A long literature analyzes the impact of 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 macroeconomic conditions, we use GDP growth in the past twelve months. For industry conditions, we study industry leverage following the spirit of Shleifer and Vishny (1992): if the alternative users of certain assets are primarily from the same industry, then liquidation values are likely to fall when firms in the industry have constrained capacity to purchase due to high indebtedness.

For this analysis, it can be useful to understand the scope of alternative users for a given type of assets: are they economy-wide, mostly in a few industries, or difficult to find in any case? Accordingly, we identify assets that are industry-specific, firm-specific, or neither. Specifically, there can be four types of assets: a) assets that are neither firm-specific nor industry-specific (e.g., vehicles); b) assets that are industry-specific but not firm-specific (e.g., aircraft, ships, railroad equipment, oil and gas equipment, nuclear fuel); c) assets that are firm-specific but not necessarily industry-specific (e.g., fabricated metal products, electronic devices, warehouses); d) assets that are both firm-specific and industry-specific (e.g., communication structures and equipment). In the data, we start with each type of asset in the BEA fixed asset table: we designate an asset as industry-specific if the concentration measured as the Herfindal index of the asset is in the top tercile;[7] we designate an asset as firm-specific if the customization measure (design costs in total production costs) is in the top tercile. After assigning each of the 71 assets in the BEA fixed asset table into one of the four categories, we calculate the (value-weighted) share of an industry's assets that belong to each category. Internet Appendix Table IA5 also shows the summary statistics of the fraction of assets that belong to each category.

In Table 3, Panel B, we use the PPE liquidation recovery rate of in each case to study the impact of time-varying macro conditions and industry conditions. We control for industry fixed effects, and merge in GDP growth rate and industry leverage at the time of the filing. For the impact of macroeconomic conditions, column (1) shows that, on average, there is a weak positive correlation between GDP growth and PPE liquidation recovery rates. Nonetheless, column (2) shows that a strong positive relationship does exist when a high fraction of assets are neither firm-specific nor industry-specific. In other words, when assets are both standardized and widely used across the economy, the liquidation recovery rate is most sensitive to general economic conditions. For the impact of industry conditions, column (3) shows that, on average, there is a borderline significantly negative relationship between industry leverage and PPE liquidation recovery rates. Nonetheless, column (4) shows that industry leverage is very relevant for industries that have a larger share of assets that are industry-specific but not firm-specific. In other words, when assets are primarily

[7] The value is one if all of the asset is used in one industry, and close to zero if the asset is equally split among different industries.

used in a given industry but not necessarily customized to a particular firm, the liquidation recovery rate is most sensitive to industry conditions.

Overall, when natural buyers of PPE are economy-wide (i.e., assets are neither firm-specific nor industry-specific), macro conditions affect liquidation recovery rates the most. When natural buyers of PPE are concentrated within an industry (i.e., assets are not firm-specific but industry-specific), industry conditions affect liquidation recovery rates the most. When there are few natural buyers of PPE on a standalone basis to begin with (i.e., assets are customized and firm-specific), macro and industry conditions appear less relevant.

Based on these estimates, we can also evaluate how much industry conditions need to change to bring PPE liquidation recovery rate from the highest industries (e.g., transportation services at around 69%) to the median (e.g., a typical manufacturing industry at around 33%). To induce a 35 percentage point change, in a typical industry, leverage would need to increase by 140 percentage points ($0.35/0.25 = 1.4$). If an industry were to have 100% industry-specific but not firm-specific assets, industry leverage would need to increase by 19 percentage points ($0.35/(2.52 - 0.70) = 0.19$). Accordingly, there appears to be substantial cross-industry variation in asset specificity, which is not easily offset by time-varying conditions within an industry.

4 Basic Implications

After analyzing the determinants of asset specificity, we study the basic implications of asset specificity in this section, with a focus on investment activities. These tests shed light on several research topics, and further demonstrate the informativeness of our data.

It is also natural to ask how asset specificity affects debt contracts and borrowing capacity. We study these issues in a companion paper (Kermani and Ma, 2020). We show that asset specificity and liquidation values do not affect the total amount of borrowing (e.g., total book leverage) for large firms and firms with positive earnings. Asset specificity and liquidation values do have a significant positive relationship with the total amount of borrowing for small firms and firms with negative earnings. Meanwhile, asset specificity does affect the composition of debt: firms with higher liquidation values have more asset-based debt (lending on the basis of the liquidation value of discrete assets like PPE, inventory, etc.), while firms with lower liquidation values have more cash flow-based debt (lending on the basis of firms' going-concern value and operating earnings) and debt with strong control rights. The results are consistent with the observations in Lian and Ma (2020) about the importance of cash-flow based lending among non-financial firms in most industries. When firms have positive earnings (most large firms), total debt capacity is typically driven by earnings-based borrowing constraints, instead of liquidation values of discrete assets.

Our analyses in the following focus on implications of asset specificity for investment activities (instead of financing decisions). In Section 4.1, we examine implications from classic investment theories with irreversibility: when asset specificity is high, firms have less flexibility in downsizing and investments are more irreversible, which can induce a higher sensitivity of investment activities to uncertainty. Frictions in capital adjustment may also affect pricing behavior. In Section 4.2, we analyze implications from the growing literature on the impact of rising intangibles.

4.1 Traditional Investment Theories

Below we investigate the basic implications of asset specificity in investment theories. We first show how asset specificity affects investment activities, including the prevalence of disinvestment and the response of investment to uncertainty. We then study the link between asset specificity and pricing behavior, as well as the relationship with productivity dispersion.

4.1.1 Investment Behavior

When asset specificity is higher, disinvestment is more costly. Classic models of investment irreversibility predicts that investments would also be more sensitive to uncertainty, which we test using investments in both fixed assets and inventory.

Prevalence of Disinvestment

We first verify that disinvestment is less common when asset specificity is higher. For instance, when PPE has low liquidation value, firms lose more from directly selling it, which should lead to a lower prevalence of selling PPE on a standalone basis.

For firms in Compustat, we can measure the prevalence of PPE sales using information from the variable "Sale of Property, Plant, and Equipment" (SPPE), which documents proceeds from PPE sales. We can 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 2 plots the average frequency (Panel A) and amount (Panel B) of PPE sales per year in each 2-digit SIC industry on the y-axis, and the industry-average PPE liquidation recovery rate on the x-axis. We see that it is more common to observe PPE sales in industries with lower PPE specificity (higher recovery rates). Internet Appendix Figure IA3 shows the corresponding plots using predicted PPE recovery rates based on physical attributes (using Table 3, Panel A, column (1)), and the patterns are similar. Table 4 shows the relationship in regressions, using both the raw industry-average PPE recovery rates and PPE recovery rates predicted by the physical attributes of PPE in each industry (mobility, durability, and standardization/customization). A one standard deviation increase in industry-average PPE recovery rate is associated with a roughly 0.31 standard deviation increase in the average frequency of PPE sales (based on column (1)), and a roughly 0.56 standard deviation increase in the average amount of PPE sold (based on column (4)).

For industries with high asset specificity, we find that capital reallocation primarily takes the form of mergers and acquisitions: purchases of firms or segments as a whole (installed assets together with teams and organizational structures), instead of capital on a standalone basis. In other words, when assets are specialized, it is important to combine them with human capital and organizational capital, and assembling human capital and organizational capital is not frictionless. While such firms can potentially downsize through selling an entire division or segment, these changes are inevitably lumpier and more drastic. Consequently, overall firms with more specialized assets would have less flexibility for disinvestment and face higher investment irreversibility.

Impact of Uncertainty

A key implication of investment irreversibility is that investments are sensitive to uncertainty shocks (see Bloom (2014) for a summary). We test this prediction in Table 5. We use firm-level uncertainty shocks based on high-frequency stock returns data, similar to the measure in Gilchrist, Sim, and Zakrajšek (2014). In particular, we study annual regressions:

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

where $\sigma_{i,t}$ denotes the return volatility of firm i in year t, and λ_i denotes the liquidation recovery of firm i's assets based on its industry. The outcome $Y_{i,t+1}$ is the investment rate in year $t+1$ to allow for lags in investment implementation: investment decisions may translate into actual investment spending with a delay (Lamont, 2000). The control variables $X_{i,t}$ include Q, book leverage cash holdings, EBITDA, and size (log book assets) at the end of year t. We include firm fixed effects (α_i) and industry-year fixed effects ($\eta_{j,t}$), and double-cluster standard errors by firm and time. To allow for more variation in uncertainty, we use a longer sample of 1980 to 2016.

Table 5, Panel A, columns (1) to (4) study capital expenditures (CAPX investment) on the left hand side, which represent spending on PPE (normalized by lagged net PPE). We interact PPE liquidation recovery rate (λ) with firm-level return volatility (σ). In columns (1) and (2), we find that higher uncertainty is associated with significant decreases in capital expenditures when PPE recovery rates are low, but not when PPE recovery rates are high. Indeed, when the PPE recovery rate is zero, the coefficient on volatility (β) is significantly negative; when the PPE recovery rate is one, the coefficient on volatility ($\beta + \phi$) becomes roughly zero. In columns (3) and (4), we instrument PPE recovery rates using predicted values based on physical attributes measured in Section 3.1, and the results are similar.

Table 5, Panel A, columns (5) to (8) study inventory investment, which a large literature finds to be important for economic fluctuations as well (see Ramey and West (1999) for a summary). We interact inventory liquidation recovery rate (λ) with firm-level return volatility (σ). Similarly, we find that higher uncertainty is associated with significant decreases in inventory investment when inventory recovery rates are low, but not when inventory recovery rates are high. We can also instrument inventory recovery rate using predicted values based on the physical attributes of inventory discussed in Internet Appendix Section IA4, and the results are similar.

Furthermore, in Table 5, Panel B, we find that the sensitivity of CAPX investment to uncertainty is affected by PPE recovery rates, but not by inventory recovery rates. Conversely, the sensitivity of inventory investment to uncertainty is affected by inventory recovery rates, but not by PPE recovery rates. This finding provides further evidence that the liquidation recovery rates of different types of assets capture their disinvestment costs (instead of proxying for the severity of financial frictions the firm faces).

4.1.2 Pricing Behavior

Woodford (2005) and Altig et al. (2011) point out that when capital is firm-specific (instead of generic and available from an economy-wide rental market), firms can display higher price stickiness. 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 6, we collect information on industry-level price rigidity using the frequency of price change data from Nakamura and Steinsson (2008).[8] We match and aggregate this data to 2-digit SICs, and study the relationship with industry-level asset specificity. Given that in practice both PPE and inventory can be relevant for production, we investigate the connection with the specificity of PPE and inventory. Columns (1) and (2) show that in industries where asset specificity is lower (i.e., recovery rate is higher, or fraction of firm-specific PPE as defined in Section 3 is lower), prices appear more flexible. In column (3) we combine the specificity of different types of assets and compute the firm-level total liquidation value from PPE and working capital (normalized by book assets) as in Section

[8]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.

2.4. The independent variable is then the industry average of firm-level liquidation value. Again, we see that in industries where overall firm-level liquidation values are higher (i.e., assets more generic), prices are more flexible. Conversely, in industries where overall firm-level liquidation values are lower (i.e., assets more specific), prices appear stickier. Figure 3 visualizes this relationship by plotting the industry-level frequency of price change on the y-axis and the industry-average firm liquidation value on the x-axis. Finally, in column (4) we also "instrument" firm-level total liquidation value using the physical attributes of PPE (described in Section 3.1) and inventory (described in Internet Appendix Section IA4), and the results are similar.

In Internet Appendix Tables IA9 and IA10, we also find that firms with a higher degree of asset specificity have more countercyclical markups, conditional on output gap (log real GDP minus log potential GDP) and conditional on demand shocks from defense spending using data from Nekarda and Ramey (2011). While the measurement of markups can be non-trivial and the mechanisms that affect markup cyclicality can be complicated, this stylized fact seems fairly strong.

4.1.3 Productivity Dispersion

Greater irreversibility of investments may also imply greater productivity dispersion (Eisfeldt and Rampini, 2006; Lanteri, 2018), and we show the model prediction in Lanteri (2018) in Internet Appendix Figure IA4. We present the empirical relationship in our data in Figure 4. The y-axis shows the average annual dispersion in Q within each 2-digit SIC industry (y-axis). The x-axis shows the average firm-level liquidation value of PPE and working capital (normalized by total book assets) in the industry. We use both regular Q (market value of assets over book value of assets) in Panel A and Q accounting for potential impact of intangibles from Peters and Taylor (2017) in Panel B. We see that industries with lower liquidation values tend to have higher Q dispersion. Furthermore, this holds for both large firms (total assets greater than median in Compustat each year) and small firms (total assets smaller than median). This pattern suggests that the impact of liquidation values is not necessarily through borrowing constraints, since large firms' debt capacity is not primarily driven by liquidation value (Lian and Ma, 2020; Kermani and Ma, 2020). Instead, low liquidation values can work through higher irreversibility of capital investments. Table IA2 presents the corresponding results in regressions, where we also instrument the liquidation value using the physical attributes of PPE and inventory and find similar results.

4.2 The "New Economy" and Rising Intangibles

In the above, we investigate traditional investment theories, with a focus on fixed assets. A vibrant recent literature documents that an important trend in the past few decades is the growing prevalence of intangible assets (Corrado, Hulten, and Sichel, 2009; Peters and Taylor, 2017; Haskel and Westlake, 2018; Crouzet and Eberly, 2019b,a), broadly defined as production assets without physical presence. They include identifiable intangibles such as computerized information (software, data, recordings, films), usage rights (license, exploration, route rights, domain names, etc.), patents and technologies, and brands, which could be separable and transferable to alternative users on a standalone basis. Intangible assets 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.

How does rising intangibles affect firms' asset specificity? We analyze this question in the following. For identifiable intangibles, many are transferable on a standalone basis (e.g., software, excavation rights, airlines' gate rights, patents), and our data provides some information about their liquidation recovery rates. For other intangibles that are integral to the firm (e.g., organizational capital), they cannot be separated from the firm and obtain liquidation value. As intangibles become more important over time, a natural question to ask is whether this change leads to a substantial decrease of liquidation value among firms, which is the concern in a growing number of papers (Giglio and Severo, 2012; Caggese and Perez-Orive, 2018; Haskel and Westlake, 2018; Li, 2019; Falato et al., 2020).

We provide several findings relevant for understanding the impact of rising intangibles. First, building on the discussions above, we further flesh out that physical assets of non-financial firms are already highly specific and liquidation values are low to begin with. Second, in many industries, the liquidation recovery rate of identifiable intangibles is not necessarily much lower than that of PPE, in part because intangibles do not necessarily face transportation costs given the absence of physical presence. Third, based on existing measures of intangible assets, the rise in intangibles is more pronounced in industries where physical assets are more specific (PPE liquidation recovery rate is lower) in the first place. Taken together, we find that the impact of rising intangibles on firms' asset specificity and liquidation values has been relatively limited so far.

Specifically, we proceed in three steps. First, as shown in Section 2, physical assets are already quite specific in many industries. For instance, the mean industry-level liquidation recovery rate for PPE is about 33%. In this case, even if PPE is increasingly replaced by intangible assets with minimal liquidation recovery rates, the change in the total liquidation value may not be substantial.

Second, we investigate the liquidation recovery rate of identifiable intangibles. In particular, our data includes the estimated liquidation recovery rate of book intangibles, which are intangible assets acquired from external parties and therefore capitalized on balance sheet based on the current accounting rules in the US. Intangible assets developed internally, on the other hand, are expensed rather than capitalized under US accounting rules, and do not show up among book assets. Book intangibles have two components. The first component mainly represents identifiable intangibles (such as software, customer data, usage rights, patents, among others), which can be acquired independently from external parties. This part generally has positive liquidation recovery rates. The second component is goodwill (i.e., the premium between the total purchase price in an acquisition and the net book value of all identifiable assets, which may come from the value of human capital, organizational capital, or from over-pricing), and has zero liquidation value almost by definition.

Figure 5 plots the average liquidation recovery rate of PPE versus book intangibles for Fama-French 12 industries. For each industry, the first bar represents the average PPE recovery rate; the second bar represents the average book intangible recovery rate; the third bar represents the implied recovery rate of non-goodwill book intangibles, calculated as the average book intangible recovery rate divided by one minus the industry-average share of goodwill in total book intangibles. We see that the second bar, and especially the third bar, are not much lower than the first bar. For 2-digit SIC industries, the mean industry-level recovery rate of book intangibles is about 16%, with an inter-quartile range from 2% to 25%; the mean industry-level recovery rate of non-goodwill book intangibles is about 35%, with an inter-quartile range from 4% to 59%. The level of non-goodwill book intangible recovery rates is almost comparable to that of PPE recovery rates, although with more variance.[9] In sum, identifiable intangibles can obtain liquidation values on their own, and may not necessarily be more specific than tangible assets like PPE.

Third, we find that rising intangibles seem especially pronounced in industries where physical assets are more specific in the first place. We measure the stock of intangibles in several ways. One is the BEA's estimate of the stock of intellectual property for each BEA industry (relative to BEA's estimate of the stock of fixed assets in the industry). Another is Peters and Taylor (2017)'s estimate of the stock of intangibles for Compustat firms (relative to their net PPE), which includes both book intangibles and the estimated stock of off-balance sheet intangibles. Peters and Taylor (2017) capitalize R& D spending to estimate

[9] To put the level of intangible recovery rate in perspective, we may need to bear in mind several factors. One is that given the eligibility criteria for book intangibles (i.e., acquired from external parties), they may select for intangible assets that are easier to trade and purchase, and select for those with higher liquidation recovery rates. Another is that the market for trading intellectual properties and other identifiable intangibles (various types of rights) is developing over time (Mann, 2018), so intangible recovery rates in the future may be enhanced as more markets develop and mature.

knowledge capital, and capitalize 30% of Selling, General, and Administration expenses to estimate organizational capital. They then combine these values with book intangibles to form an estimate of the total stock of intangibles. Although these measures could be imperfect, the pattern we document is fairly robust to the measurement of intangibles.

Figure 6 plots the change in the industry-level share of intangible assets relative to the sum of PPE and intangibles from 1996 and 2016 (y-axis) against industry-level PPE 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 direct measurement of PPE recovery rates and PPE recovery rates instrumented by physical attributes of PPE. In all cases, industries with low PPE recovery rates have seen the most substantial increase in the relative prevalence of intangibles. In other words, even if intangibles have lower liquidation values, the shift from physical assets like PPE to intangibles has been greater where PPE's recovery rates are already small, and there is not much to "lose" further.

Putting these observations together, Figure 7 shows the estimated liquidation value of all Compustat firms, as a share of total book value (Panel A) and as a share of total enterprise value (Panel B), from 1996 to 2016. 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 (Crouzet and Eberly, 2019b). Indeed, the sum of liquidation value from PPE and book intangibles (the bottom two bars) has stayed roughly constant (and always below 20% of both book value of assets and firm enterprise value).

Accordingly, based on our data, it does not appear that rising intangibles has led to a significant drop in firms' liquidation values. Correspondingly, it is not necessarily the case that rising intangibles substantially tighten firms' borrowing constraints as many papers have feared. Furthermore, in the US, firms' debt capacity is not necessarily tied to the liquidation value of particular assets (Kermani and Ma, 2020; Lian and Ma, 2020), especially when firms have positive earnings. Similarly, the results also suggest that it is not clear whether irreversibility increases significantly with rising intangibles. A set of indentifiable intangibles such as usage rights, customer lists, certain patents, etc. could be reasonably sold off and such investments could be partially reversible.

What then is different about intangibles? An interesting hypothesis is that intangibles can be more "scalable" (Haskel and Westlake, 2018; Crouzet and Eberly, 2019b). Given that intangibles are not bound by physical presence and physical locations, some intangibles could be used simultaneously at multiple places (e.g., enterprise planning systems, brands, data). This effect may lead to higher concentration and the prominence of "superstar" firms. In addition, rising intangibles may also lead to an apparent decline in investment activities measured using traditional capital expenditures, which is relevant for national accounting and understanding economic dynamism (Corrado, Hulten, and Sichel, 2005; Crouzet and Eberly, 2019a). These implications of rising intangibles are likely to be more central than changes in liquidation values.

5 Connections to Model Parameters

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

5.1 Models of Investment Irreversibility

Models of investment irreversibility often need to calibrate or estimate the loss from disinvestment of the capital stock. In particular, this class of models postulate 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). 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 old 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 measurement suggests that if capital reallocation takes the form of directly selling used 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 capital and organizational capital, the loss may not be as substantial, but such adjustments are inevitably much lumpier and are difficult to implement if the 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.[10] In other words, firms' borrowing b is restricted by the liquidation value of the capital stock K, $b \leq \lambda K$, where λ is the liquidation recovery rate. Although in prior work we document that this form of borrowing constraint may not be first-order for major US non-financial firms (Lian and Ma, 2020), it could be relevant for small firms or firms with negative earnings. Thus modeling applications may still find the liquidation value estimates to be relevant in these settings.

Models of "collateral constraints" seem to 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, Chaney, Huang, Sraer, and Thesmar (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 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 (2020), 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' going-concern cash flow value) instead of asset-based lending (i.e., lending on the basis of the liquidation value of separable assets like PPE). Correspondingly, total debt capacity may not necessarily reflect the tightness of the traditional collateral constraints. On the other hand, when models target the sensitivity of borrowing to real estate value as in Catherine et al. (2019), they are more likely to infer how much firms can borrow from pledging fixed assets for asset-based lending.

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. It is typically bounded by the liquidation recovery rate, which is 33% for PPE in the average industry based on our data. According to lenders, they also generally lend 25% to 30% of the book value of industrial PPE for asset-based debt. Correspondingly, for models where firms can only borrow against the liquidation value of their fixed assets, the low level of debt capacity would apply for most industries.

6 Conclusion

Asset specificity is a central issue in many lines of research. Obtaining systematic measures of the level of asset specificity across industries has been a long-standing challenge. We

[10] We use "collateral constraints" in quotes as a reference to the common academic use of the term, where "collateral" implies separable and often tangible assets (like real estate) that creditors may want to seize and liquidate. Under US law, collateral in practice can take 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 they want to seize.

tackle this challenge by constructing a new dataset that measures the liquidation recovery rates of all major asset categories across industries.

We find that non-financial firms' assets are generally highly specific. For instance, in the average industry, the liquidation recovery rate of a firm's plant, property, and equipment (PPE) is about 33%. We also investigate the key determinants of variations in asset specificity. We find that physical attributes of assets used in different industries have a strong link with cross-industry variations in asset specificity. We collect a rich set of data to measure physical attributes such as mobility, durability, and standardization, and show that they can account for at least around 40% of the variation in industry-average PPE liquidation recovery rates. We also find that macro conditions affect PPE recovery rates the most for industries with a large share of PPE that is neither industry-specific nor firm-specific. Industry conditions affect recovery rates the most when a large share of PPE is industry-specific but not firm-specific. When PPE is customized and firm-specific, there are few alternative users who want to directly purchase such PPE in any case, and recovery rates are less responsive to macro or industry conditions.

We then show that the data on asset specificity has broad applications for macro-finance questions. It aligns closely with firms' investment behavior, such as the prevalence of disinvestment and the investment sensitivity to uncertainty shocks, as predicted by classic theories of investment irreversibility. It also helps understand patterns in price setting and productivity dispersion, generally in line with model predictions as well. Furthermore, the data suggests that the first-order impact of rising intangibles may not be to compress firms' liquidation values. Other implications of rising intangibles, such as the impact on scalability, could be more interesting and they may interact with the attributes of physical assets. Finally, the physical attributes of assets we measure also allow us to establish the links between asset specificity and macro-finance outcomes based on physical foundations.

Overall, we hope the data is useful for informing key parameters in models, and for testing and uncovering economic mechanisms.

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Main Figures and Tables

Figure 1: Liquidation Analysis Reporting Examples

This figure shows examples of summary tables in liquidation analysis in Chapter 11. 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

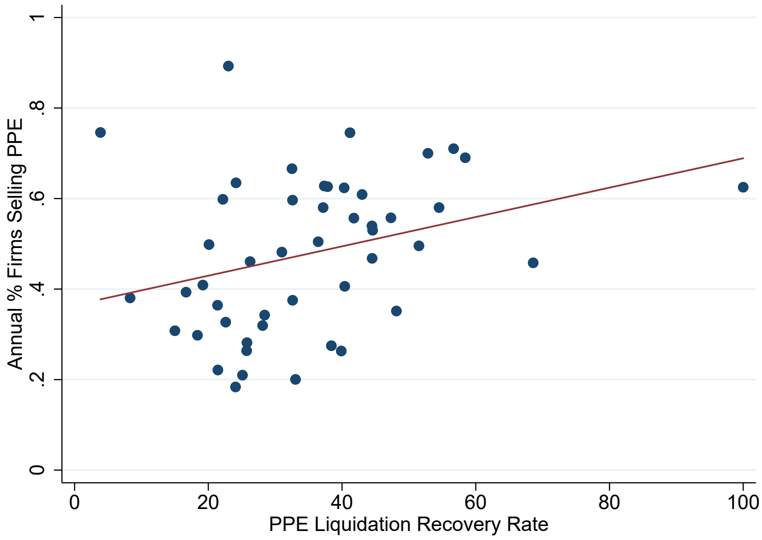
Panel B. Sorenson Communications

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**

Figure 2: PPE Liquidation Recovery Rates and Prevalence of PPE Sales

The x-axis is the industry-average PPE liquidation recovery rate. The y-axis is the industry-average frequency of having non-zero PPE sales in Panel A, and the industry-average PPE sale value (normalized by lagged net PPE) in Panel B. Sample period is 1996 to 2016.

Panel A. Frequency of PPE Sales



Panel B. PPE Sold/Net Book PPE

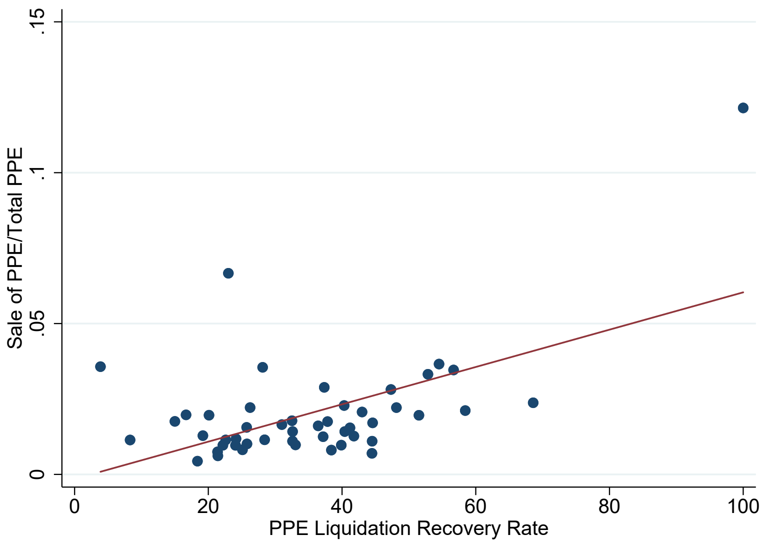


Figure 3: Asset Specificity and Frequency of Price Change

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, based on data from Nakamura and Steinsson (2008) (% price change per month). Each industry is a 2-digit SIC.

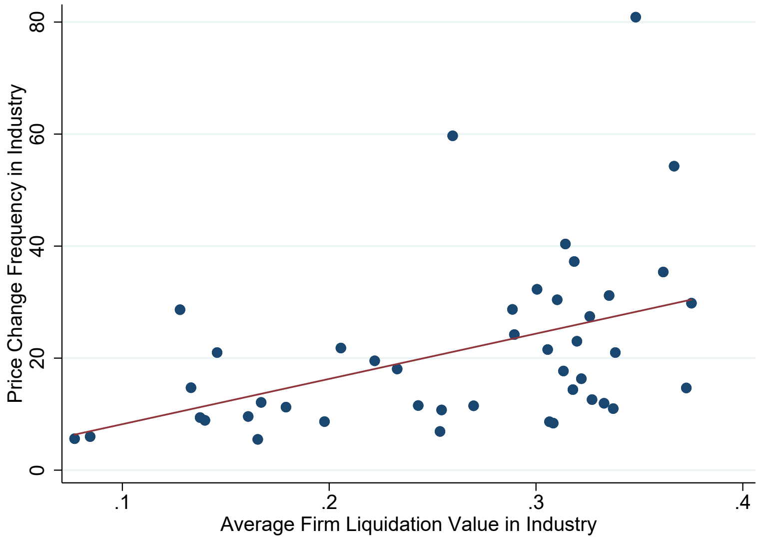
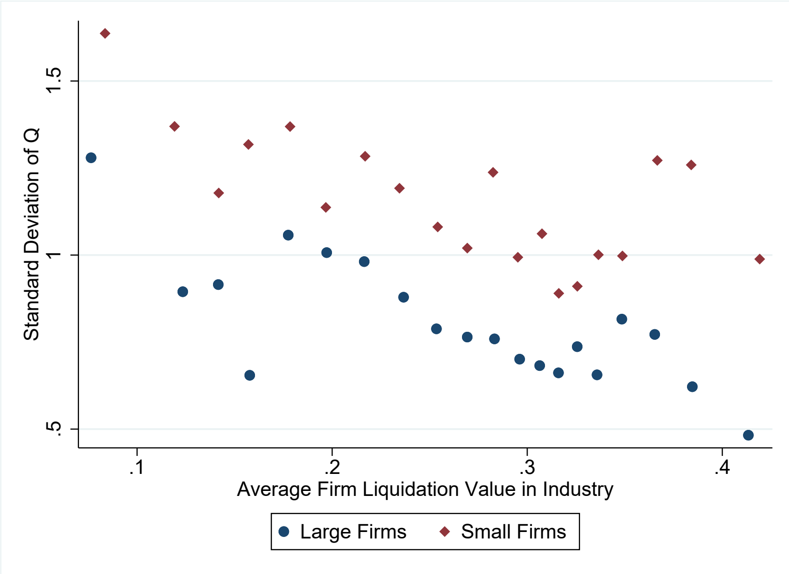


Figure 4: Asset Specificity and Dispersion of Q

This figure shows binscatter plots of industry-level dispersion in Q. We calculate cross-sectional standard deviation of Q for each 2-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. Sample period is 1996 to 2016.

Panel A. Standard Average Q



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

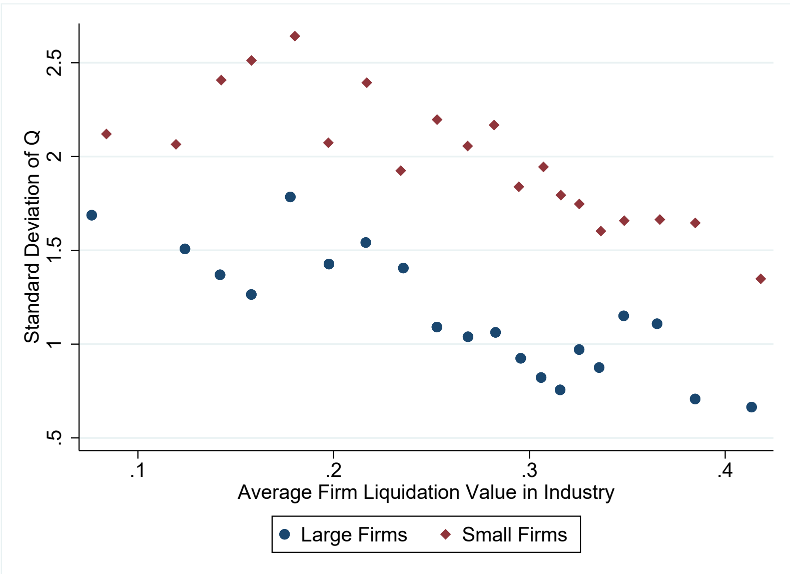


Figure 5: Industry-Average Recovery Rate: PPE vs. Book Intangibles

This figure shows the average recovery rate of PPE versus book intangibles in each Fama-French 12 industry (except financials). For each industry, the first bar shows the mean PPE recovery rate. The second bar shows the mean book intangible recovery rate. The third bar shows the estimated book intangible recovery rate excluding goodwill, which is calculated as the mean book intangible recovery rate divided by one minus the share of goodwill in book intangibles in the industry. In other words, we assume (as is generally the case) that the liquidation recovery rate of goodwill is zero. Then all the liquidation value of book intangibles come from non-goodwill assets.

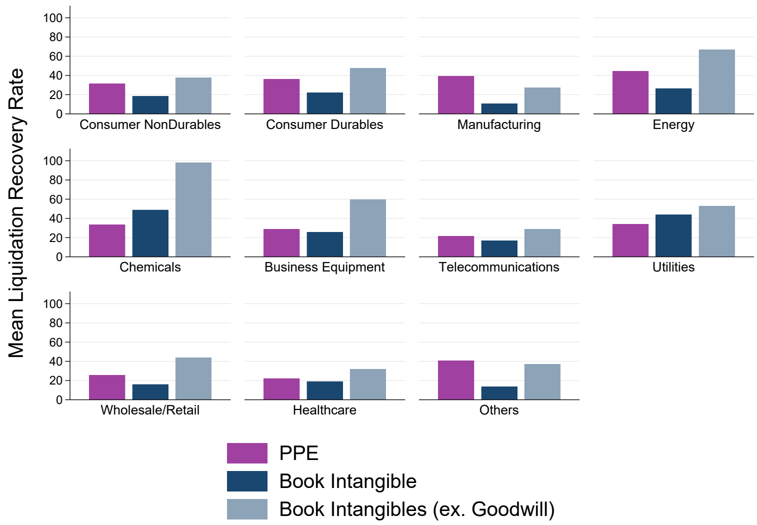
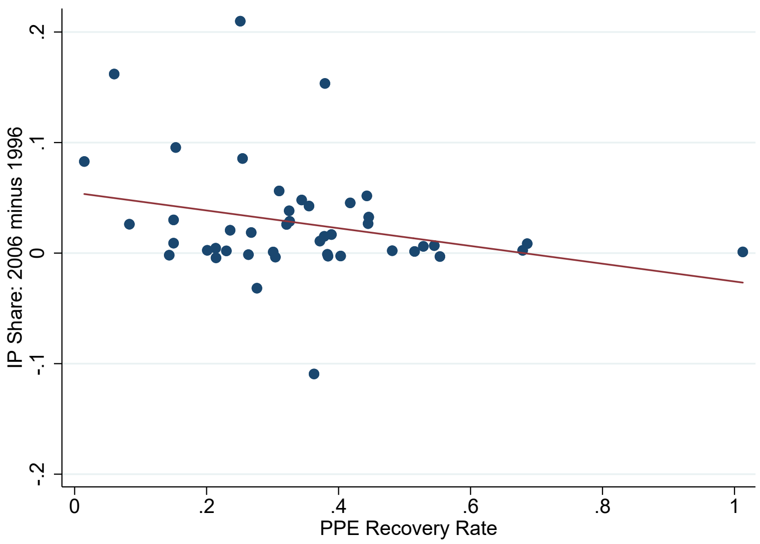


Figure 6: PPE Specificity and Rising Intangibles

Binscatter plots of rising intangibles for different levels of PPE recovery rate. Panel A uses BEA's estimates of intellectual property assets in each BEA sector, and the y-axis is the change in intellectual property as a share of intellectual property plus fixed assets from 1996 to 2016. The x-axis is the estimated average PPE recovery rate in each BEA sector. 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. The y-axis is the firm-level change in the capitalized intangibles as a share of capitalized intangibles plus net PPE from 1996 to 2016. The x-axis is the PPE recovery rate of the firm based on its industry.

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



Panel B. Firm-Level Intangibles (Compustat, Peters and Taylor (2017))

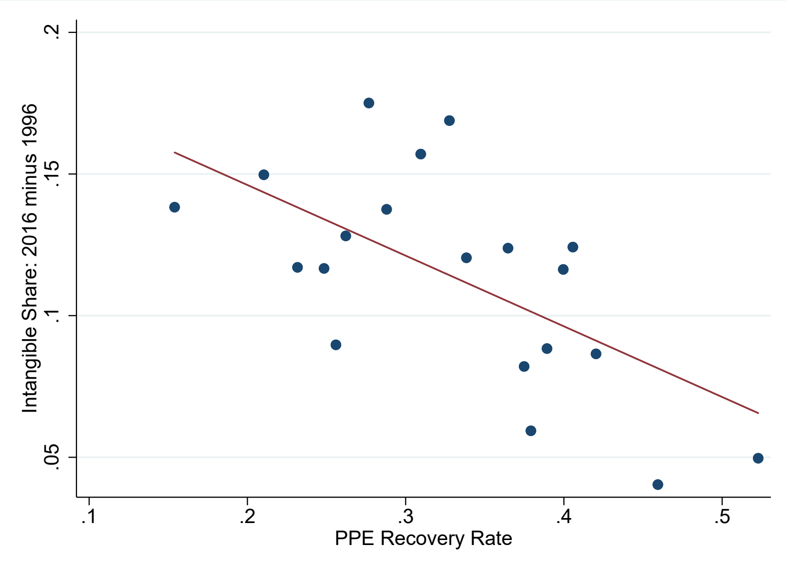
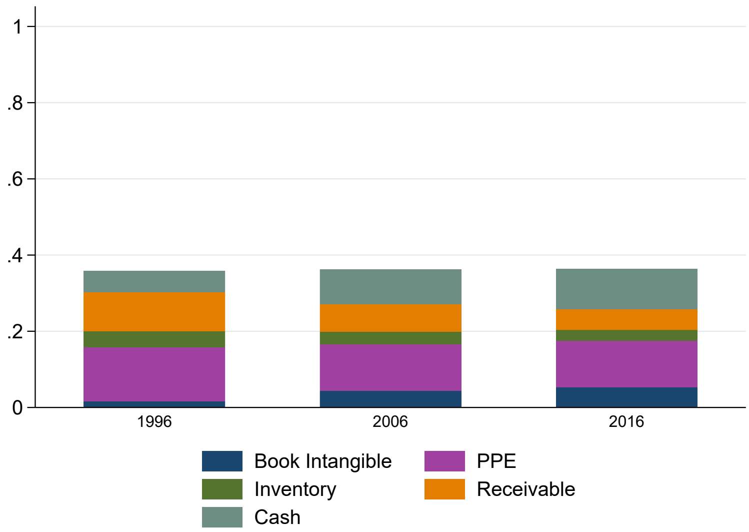


Figure 7: Estimated Firm-Level Liquidation Value and Composition Over Time (Compustat Aggregate)

This figure shows the estimated total liquidation value from PPE, working capital, book intangibles, and cash of 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.

Panel A. Total Liquidation Value over Total Book Assets



Panel B. Total Liquidation Value over Total Enterprise Value

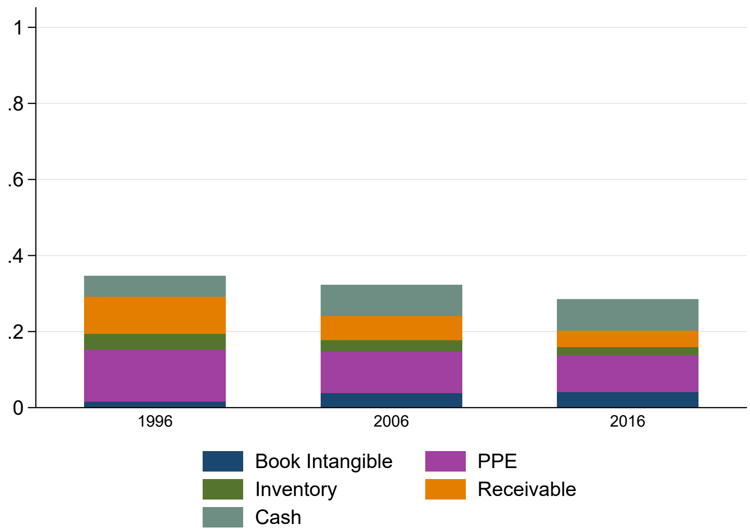


Table 1: Summary of Industry-Average Recovery Rates

This table presents summaries of industry-average recovery rates. Each industry is a 2-digit SIC code.

Panel A. Plant, Property, and Equipment (PPE)
Mean: 0.33; 75th: 0.43; 25th: 0.24 High: Transportation (0.69), Lumber (0.58), Wholesale (0.57) Low: Personal services (0.08), Educational services (0.15)
Panel B. Inventory
Mean: 0.44; 75th: 0.56; 25th: 0.32 High: Auto dealers (0.88), Apparel stores (0.75), Supermarkets (0.75) Low: Restaurants (0.14), Special construction (0.2), Communications (0.26)
Panel C. Receivable
Mean: 0.63; 75th: 0.71; 25th: 0.55 High: Utilities (0.90), Medical/optical devices (0.89), Coal (0.79) Low: Airlines (0.37), Educational services (0.37)

Table 2: Summary Statistics of Compustat Firms

Panel A shows the statistics of firm-level liquidation value estimates, which combine book value of assets with liquidation recovery rates based on the firm's industry (2-digit SIC). Liquidation values are normalized by total book assets. Panel B shows other basic statistics. The sample covers annual data from 1996 to 2016.

Panel A. Liquidation Value Statistics

Variable	mean	p25	p50	p75	s.d.	N
Liquidation value: PPE, inventory, receivable	0.23	0.12	0.23	0.33	0.13	107,378
Liquidation value: PPE, inventory, receivable, cash	0.44	0.30	0.41	0.54	0.20	106,482
Liquidation value: PPE	0.09	0.02	0.05	0.12	0.09	110,222
Liquidation value: inventory	0.05	0.00	0.02	0.07	0.07	110,523
Liquidation value: receivable	0.09	0.03	0.07	0.13	0.09	112,031
Cash/assets	0.21	0.02	0.10	0.31	0.25	117,588

Panel B. Other Statistics

Variable	mean	p25	p50	p75	s.d.	N
Log assets	4.80	3.08	4.94	6.76	2.83	118,594
Log market cap	5.58	4.02	5.54	7.03	2.14	81,687
EBITDA	278.91	-1.12	9.39	102.53	1592.02	118,305
EBITDA/l.assets	-0.19	-0.06	0.09	0.17	1.49	108,705
Debt/assets	0.35	0.02	0.21	0.41	0.77	116,929
Q	2.05	1.10	1.49	2.32	1.67	79,937
MTB	2.92	1.12	1.96	3.53	3.88	79,824
PPE/assets	0.25	0.06	0.17	0.39	0.24	115,734
Inventory/assets	0.10	0.00	0.04	0.17	0.13	116,212
Receivable/assets	0.15	0.04	0.11	0.21	0.14	117,754

Table 3: Determinants of PPE Recovery Rates

This table examines the determinants of PPE recovery rates. Panel A studies the relationship between the physical attributes of assets in each industry and industry-average PPE recovery rate. Transportation cost (in total production cost of PPE) measures mobility. Depreciation rate measures durability. Design cost share (in total production cost of PPE) measures standardization/customization. Sales share of industry in Compustat and value added share of industry in BEA data capture industry size. All attributes are measured using BEA input-output table or Compustat data in 1997. Columns (1) and (2) use 2-digit SICs; columns (3) and (4) use BEA sectors. Panel B studies the relationship between macroeconomic and industry conditions and firm-level recovery rate within each industry. Past 12-month GDP growth and industry leverage are measured as of the quarter of bankruptcy filing. 2-digit SIC industry fixed effects are included. R^2 does not include industry fixed effects.

Panel A. Physical Attributes and Industry-Average Recovery Rates

	Industry-level PPE Recovery Rate			
	Industry Classification			
	2-digit SIC		BEA sectors	
Transportation cost	-0.47***	-0.48***	-0.48***	-0.56***
	(0.12)	(0.12)	(0.12)	(0.13)
Depreciation rate	-0.55***	-0.56***	-1.62**	-1.83**
	(0.19)	(0.19)	(0.73)	(0.76)
Design cost share	-1.70**	-1.85**	-2.47**	-2.49**
	(0.83)	(0.86)	(0.95)	(0.94)
Industry sales share		0.41		
		(0.58)		
Industry value-added share				1.48
				(1.12)
Constant	1.00***	1.03***	1.13***	1.16***
	(0.21)	(0.22)	(0.19)	(0.19)
Obs	48	48	45	45
R^2	0.39	0.39	0.29	0.33

Robust standard errors in parentheses

Panel B. Impact of Time-Varying Macroeconomic and Industry Conditions

	Case-level PPE Recovery Rate			
	(1)	(2)	(3)	(4)
GDP gr	0.28	-2.05		
	(0.58)	(3.56)		
GDP gr × % non-ind spec, non-firm spec		8.46**		
		(3.80)		
GDP gr × % ind spec, non-firm spec		3.15		
		(3.19)		
GDP gr × % non-ind spec, firm spec		-7.77		
		(5.15)		
Industry lev			-0.25	0.70
			(0.20)	(0.96)
Industry lev × % non-ind spec, non-firm spec				-1.23
				(1.19)
Industry lev × % ind spec, non-firm spec				-2.52***
				(0.58)
Industry lev × % non-ind spec, firm spec				0.60
				(2.41)
Fixed effect	Industry			
Obs	353	353	353	353
R^2	0.001	0.018	0.003	0.014

Standard errors in parentheses, double-clustered by industry and time

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

The left-hand-side 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). The right-hand-side is raw industry-average PPE liquidation recovery rates when "IV" is labeled "N," and PPE recovery rates predicted by physical attributes (mobility, durability, standardization/customization shown in Table 3, Panel A, column (1)) when "IV" is labeled "Y."

	Frequency of PPE Sales		PPE Sold/Net Book PPE	
	(1)	(2)	(3)	(4)
PPE recovery rate	0.324**	0.918***	0.062*	0.083***
	(0.133)	(0.312)	(0.033)	(0.028)
Constant	0.365***	0.156	-0.002	-0.009
	(0.060)	(0.105)	(0.011)	(0.009)
IV	N	Y	N	Y
Obs	48	48	48	48
R^2	0.10		0.31	

Robust standard errors in parentheses

Table 5: Asset Specificity and Investment Response to Uncertainty

Firm-level annual regressions: $Y_{i,t+1} = \alpha_i + \eta_{j,t} + \beta\sigma_{i,t} + \phi\lambda_i \times \sigma_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$. In Panel A columns (1) to (4), $Y_{i,t+1}$ is capital expenditures (normalized by lagged net PPE), and λ_i is the PPE recovery rate. In columns (5) to (8), $Y_{i,t+1}$ is inventory investment (changes in total inventory, normalized by lagged inventory), and λ_i is the inventory recovery rate. In columns (3) and (4), the PPE recovery rate is instrumented by the predicted recovery rate based on PPE physical attributes discussed in Section 3.1 ("IV" labeled "Y"). In columns (7) and (8), the inventory recovery rate is instrumented by the predicted recovery rate based on inventory physical attributes discussed in Internet Appendix Section IA4 ("IV" labeled "Y"). $\sigma_{i,t}$ is firm-level annual stock return volatility in columns (1), (3), (5) and (7), and annual abnormal volatility (based on the Fama-French 3-factor model) in columns (2), (4), (6), and (8). In Panel B, the variables are the same as those in Panel A columns (1), (2), (5), and (6). 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. Firm fixed effects and industry-year fixed effects are included. R^2 does not include fixed effects. Standard errors are double-clustered by firm and time. The sample period is 1980 to 2016.

Panel A. Baseline Results

	CAPX Invest Rate				Inventory Invest Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vol	-3.09***		-5.13***		-4.23***		-4.41***	
	(0.40)		(0.82)		(0.55)		(0.94)	
Vol × PPE recovery rate	3.11***		9.32***					
	(1.08)		(2.34)					
Vol × Invt recovery rate					3.85***		4.30*	
					(1.21)		(2.19)	
Abnormal vol (3-fac)		-3.26***		-5.70***		-4.46***		-5.43***
		(0.41)		(0.89)		(0.54)		(1.15)
Abnormal vol (3-fac) × PPE recovery rate		3.05***		10.43***				
		(1.11)		(2.51)				
Abnormal vol (3-fac) × Invt recovery rate						3.96***		6.29**
						(1.24)		(2.83)
IV	N	N	Y	Y	N	N	Y	Y
Fixed effect	Firm. Industry-Year.							
Obs	113,319	113,319	113,319	113,319	95,764	95,764	94,722	94,722
R^2	0.09	0.09			0.06	0.06		

Standard errors in parentheses, clustered by firm and time

Panel B. Additional Results

	CAPX		Inventory	
	(1)	(2)	(3)	(4)
Vol	-3.71***		-3.84***	
	(0.46)		(0.83)	
Vol × PPE recovery rate	2.89**		-1.29	
	(1.10)		(1.70)	
Vol × Invt recovery rate	1.67*		3.94***	
	(0.88)		(1.19)	
Abnormal vol (3-fac)		-3.86***		-4.08***
		(0.46)		(0.83)
Abnormal vol (3-fac) × PPE recovery rate		2.83**		-1.28
		(1.13)		(1.73)
Abnormal vol (3-fac) × Invt recovery rate		1.63*		4.05***
		(0.86)		(1.21)
Fixed effect	Firm. Industry-Year.			
Obs	113,319	113,319	95,764	95,764
R^2	0.09	0.09	0.06	0.06

Standard errors in parentheses, clustered by firm and time

Table 6: Asset Specificity and Price Rigidity

The left-hand-side variable is the industry-level frequency of price change, based on data from Nakamura and Steinsson (2008) (% price change per month). The right-hand-side variables include PPE recovery rates, inventory recovery rates, the fraction of PPE firm-specific following the categorization in Section 3.2, and industry-average firm liquidation values (including PPE and working capital, normalized by total book assets) as constructed in Section 2.4. In column (4), the industry-average firm liquidation value is instrumented using the predicted PPE recovery rate based on physical attributes of PPE (see Section 3.1) and the predicted inventory recovery rate based on physical attributes of inventory (see Internet Appendix Section IA4). Each industry is a 2-digit SIC.

	Frequency of Price Change in Industry			
	(1)	(2)	(3)	(4)
PPE recovery rate	3.78			
	(16.87)			
Frac of PPE firm-spec		-19.48*		
		(10.45)		
Inventory recovery rate	40.01***	40.71***		
	(10.20)	(9.32)		
Ind avg firm liq val			80.81***	57.45**
			(22.56)	(27.06)
Constant	2.40	9.22	0.13	6.40
	(4.97)	(5.82)	(4.91)	(7.38)
IV	N	N	N	Y
Obs	44	44	44	42
R^2	0.17	0.20	0.19	0.18

Robust standard errors in parentheses

Table 7: PPE Specificity and Rising Intangibles

This table shows the relationship between PPE specificity and rising intangibles. Panel A measures intangibles using BEA's estimates of intellectual property assets in each BEA sector. The left-hand-side variable is IP asset stock as a share of fixed asset plus IP asset. 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. The left-hand-side variable is intangible stock as a share of intangibles and net PPE. Columns (1) and (2) show the relationship between intangibles in 1996 and PPE specificity. Columns (3) and (4) show the relationship between intangible share change between 1996 and 2016 and PPE specificity. Columns (2) and (4) instrument PPE recovery rates using predicted values based on PPE physical attributes ("IV" labeled "Y").

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

	IP/(IP+Fixed Asset)			
	1996		2016 minus 1996	
	(1)	(2)	(3)	(4)
PPE Recovery Rate	-0.158**	-0.529**	-0.080**	-0.179**
	(0.078)	(0.224)	(0.033)	(0.078)
Constant	0.176***	0.304***	0.055***	0.089***
	(0.044)	(0.093)	(0.016)	(0.030)
IV	N	Y	N	Y
Obs	45	45	45	45
R^2	0.03		0.08	

Standard errors in parentheses

Panel B. Firm-Level Intangibles (Compustat, Peters and Taylor (2017))

	Intangibles/(Intangibles+PPE)			
	1996		2016 minus 1996	
	(1)	(2)	(3)	(4)
PPE recovery rate	-0.427	-0.711	-0.252***	-0.542***
	(0.391)	(0.581)	(0.097)	(0.166)
Constant	0.757***	0.851***	0.197***	0.293***
	(0.119)	(0.200)	(0.035)	(0.059)
IV	N	Y	N	Y
Obs	6,964	6,964	1,509	1,509
R^2	0.02		0.01	

Standard errors in parentheses, clustered by industry

Internet Appendix

IA1 Additional Figures and Tables

Figure IA1: PPE Liquidation Recovery Rates and PPE Sale Recovery Rates (Compustat)

The x-axis is the industry-average liquidation recovery rate of PPE from liquidation analysis in Chapter 11 filings. The y-axis is the industry-average sale recovery rate of PPE computed among Compustat firms. We begin with firm-years with positive PPE sale proceeds (Compustat variable SPPE). 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 positive acquisition spending, where it is difficult to tease out the change in PPE book value due to acquisitions. We compute the PPE sale recovery rate as PPE sale proceeds divided by the net book value of PPE sold. We winsorize this variable at one percent and take average in each 2-digit SIC industry (from 2000 to 2016, same as the time period for the liquidation recovery rate data), which produces the industry-level PPE sale recovery rate.

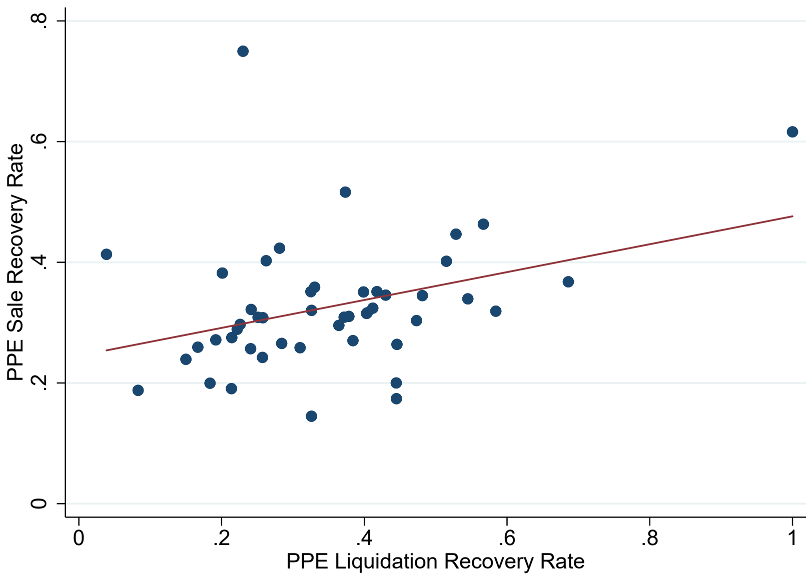
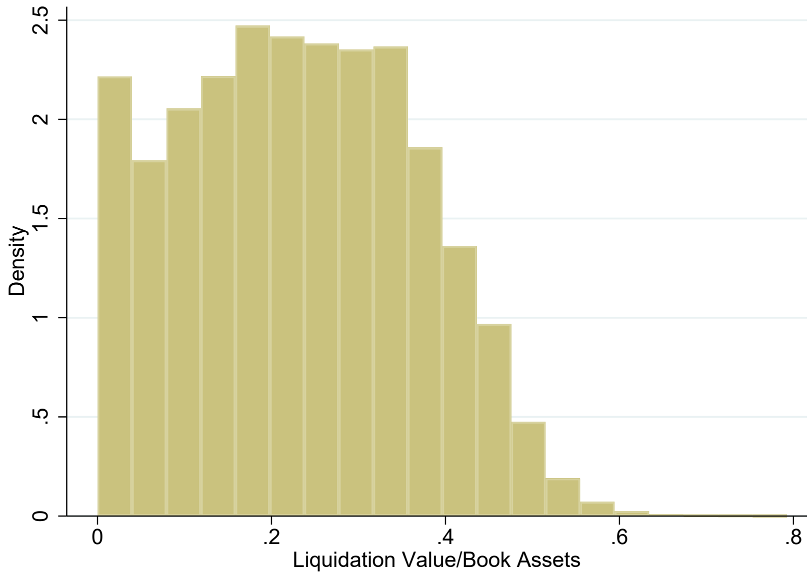


Figure IA2: Firm-Level Liquidation Value Estimates: Distribution and Composition

Panel A shows the distribution of estimated firm-level liquidation value, including PPE, inventory, and receivable, normalized by total book assets. Panel B shows the composition for the average firm. The sample period covers 1996 to 2016.

Panel A. Firm-Level Liquidation Value (PPE, Inventory, Receivable)



Panel B. Composition of Liquidation Value for Average Firm

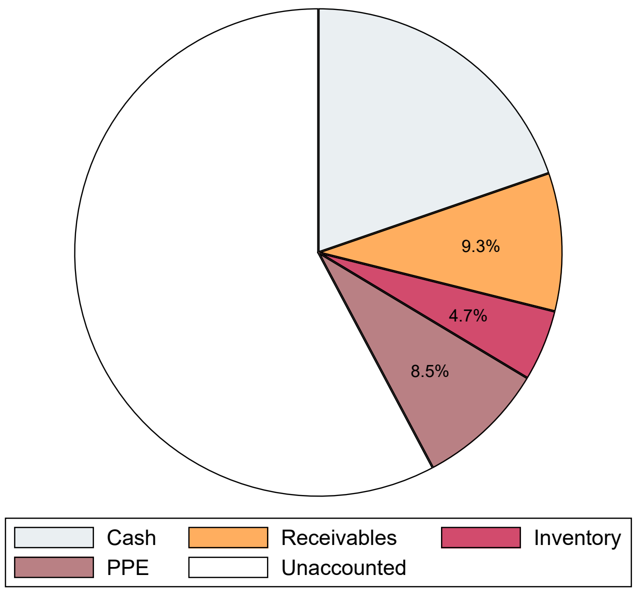
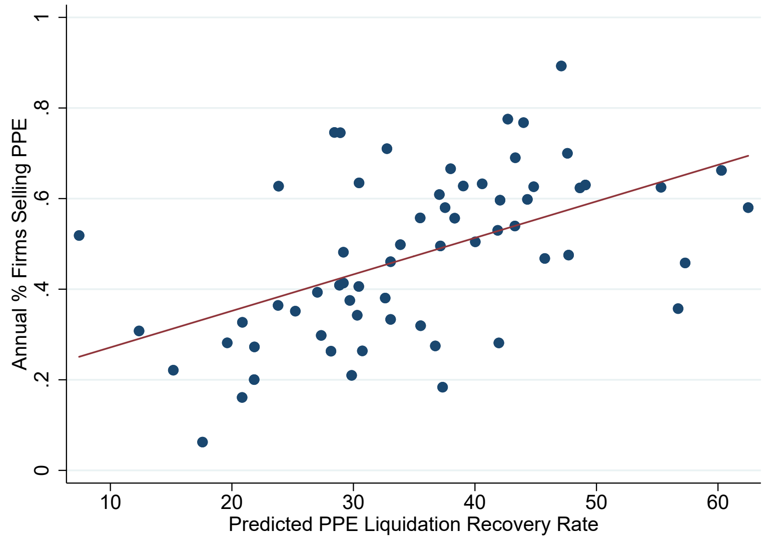


Figure IA3: PPE Liquidation Recovery Rate and Prevalence of PPE Sales

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

Panel A. Frequency of PPE Sales



Panel B. PPE Sold/Net Book PPE

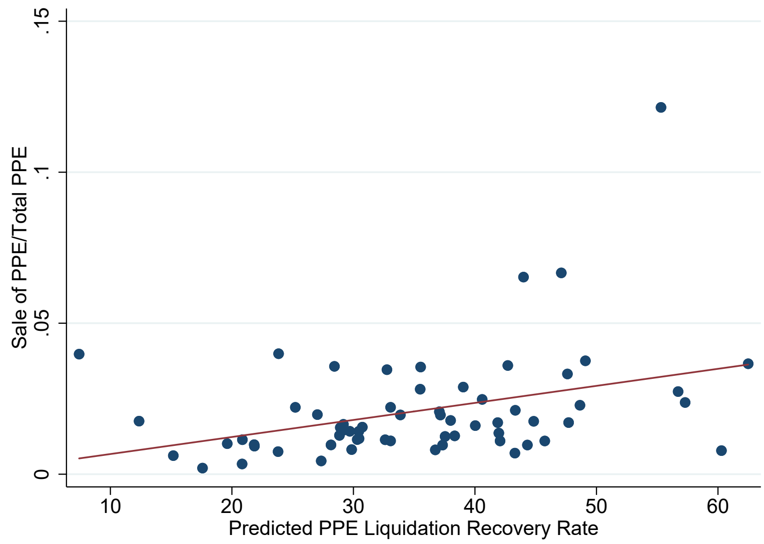


Figure IA4: Investment Irreversibility and Productivity Dispersion: Lanteri (2018)

This figure shows the relationship between MRK 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).

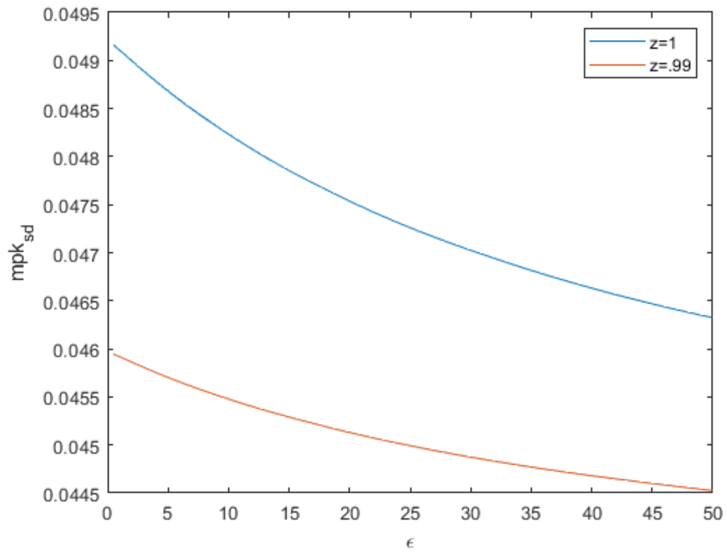


Table IA1: PPE Recovery Rates and Firm Characteristics

This table shows the relationship between PPE recovery rates and firm characteristics. In columns (1) to (3), 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 and Q from merging the cases with Compustat (we use latest annual results up to two years prior to filing). In columns (4) to (6), the dependent variable is the firm-level PPE sale recovery rate, using 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 positive acquisition spending, where it is difficult to tease out the change in PPE book value due to acquisitions. We compute the PPE sale recovery rate as 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), EBITDA, and Q. Industry fixed effects are included. R^2 does not include fixed effects.

	Liquidation Recovery Rate			Sale Recovery Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Total liabilities/assets	-0.002	0.019	0.067***			
	(0.013)	(0.024)	(0.025)			
Book leverage				-0.006	-0.008	0.009
				(0.010)	(0.011)	(0.028)
Log assets	-0.007	0.001	0.013	-0.016***	-0.016***	-0.015***
	(0.007)	(0.011)	(0.016)	(0.002)	(0.003)	(0.003)
EBITDA/l.assets		0.116**	0.065		0.003	0.081***
		(0.051)	(0.065)		(0.010)	(0.024)
Q			-0.022*			0.010***
			(0.013)			(0.004)
Fixed effect				Industry		
Obs	345	207	151	7,197	7,155	5,374
R^2	0.00	0.02	0.05	0.01	0.01	0.01

Standard errors in parentheses, clustered by industry and time

Table IA2: Q Dispersion

Industry-level annual regression, where the left-hand-side variable is annual cross-sectional dispersion in Q for each 2-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) and (2), and Q adjusted for intangibles from Peters and Taylor (2017) in columns (3) and (4). Industry-average liquidation value is the annual average firm-level liquidation value (including PPE and working capital) constructed in Section 2.4. In columns (2) and (4), industry-average liquidation value is instrumented by PPE and inventory recovery rates predicted based on their physical attributes (see Section 3.1 and Internet Appendix Section IA4 respectively). Sample period is 1996 to 2016. Year fixed effects are included. R^2 does not include fixed effects.

	Standard Q		Adjusted Q	
	(1)	(2)	(3)	(4)
Ind avg liq val	-2.00***	-1.93**	-3.43***	-2.90*
	(0.56)	(0.78)	(1.20)	(1.52)
IV	N	Y	N	Y
Fixed effect		Year		
Obs	979	945	981	945
R^2	0.11		0.09	

Standard errors in parentheses, clustered by industry and time

IA2 Liquidation Analysis Examples

In the following, we include excerpts of the detailed discussion for the summary liquidation value estimates shown in the example of Lyondell Chemical in Figure 1. They explain the procedures for the estimates for PPE, inventory, account receivable, and cash.

Figure IA5: Lyondell Chemical Example: Facility-Level Information for All PPE

This figure shows an excerpt of the discussion about PPE liquidation value estimates in the liquidation analysis of Lyondell (Panel A) and excerpt of the facility-level estimate in the accompanying appendix.

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 Facility-Level Estimate in Liquidation Analysis Appendix

LYONDELLBASELL INDUSTRIES AF S.C.A.
SUMMARY OF LIQUIDATION VALUE IN PLACE
AS OF APRIL 1, 2010
CURRENCY- USD **LIQUIDATION VALUE IN PLACE**

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: Facility-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 IA6: Lyondell Chemical Example: Other Assets

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

Panel A. Excerpt of Inventory Discussion in Liquidation Analysis

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 Cash and Receivable Discussion in Liquidation Analysis

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

Below we further explain the measurement of the physical attributes of plant, property, and equipment (PPE). As described in Section 3.1, we utilize information from BEA's fixed asset table and input-output table. First, we study which types of assets each industry uses. We collect information from BEA's fixed asset table, which shows the stock amount of 71 types of fixed assets in 58 sectors each year. Second, we measure the attributes of each of the 71 types of assets, which rely on information from 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 IA3 below.

Table IA3: List of Assets in BEA Fixed Asset Table

This table shows the 71 types of assets in the BEA Fixed Asset Table. BEA provides the stock amount (net of depreciation) for each of 58 sectors in each year.

	Code	NIPA Asset Types		Code	NIPA Asset Types
		EQUIPMENT			**STRUCTURES**
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 standardization/customization of each of the 71 types of assets, we draw on transportation cost and design cost information from BEA's input-output table. We find counterparts of the 71 types of fixed assets in the input-output table using the

PEQ bridge for equipment and hand matching for structures. We use the 1997 input-output table.

- For transportation costs, we start with the input-output "use" table. For each asset, we find all the instances where it is used as an input (recorded as "commodity"), and accordingly transported to users. We calculate the total transportation costs in all uses, and divide by the total value of the asset used (in producer prices). In other words, we calculate the share of transportation costs in total asset value.

- For design costs, we also start with the input-output "use" table. For each asset, we calculate the share of design costs in the total costs of producing it, so we find all the instances where the asset is an output. We categorize inputs with the following key words as related to design and customization: "design," "custom computer programming," "information services," "data processing services," "software," "database," "other computer related services," "architectural and engineering services," "research," "advertising," "management consulting."

  Alternatively, we can also measure the cost of design as the share of production cost not accounted for by purchasing materials (which can be measured using the accounting variable cost of goods sold). For each of the 71 types of assets, we can measure this share in its production. Results are similar with this alternative measure.

We then compute the overall transportation costs and design costs for each industry in the BEA fixed asset table, by summing up the asset-level attributes, based on the share of each asset in the industry. Accordingly, the industry-level measures capture the total transportation costs as a share of asset value for all of the industry's fixed assets, and the share of design costs in producing all of the industry's fixed assets.

Finally, we match the industries in the BEA fixed asset table with 2-digit SIC industries in our liquidation recovery rate data. The matching is listed below. For each SIC industry, we take the average of the BEA industries matched to it.

For durability, we can calculate depreciation for each BEA industry using BEA fixed asset table and match to 2-digit SICs, or directly calculate average depreciation rate in each 2-digit SIC industry using Compustat. In the baseline results, we use the latter approach, which avoids industry conversion.

Table IA5 presents industry-level (2-digit SIC industries) summary statistics of the physical attributes: mobility (transportation cost as a share of PPE production cost), durability (depreciation rate), standardization/customization (design cost share in PPE production cost). It also shows statistics for the share of the four categories of PPE discussed in Section 3.2: a) assets that are neither firm-specific nor industry-specific (e.g., vehicles); b) assets that are industry-specific but not firm-specific (e.g., aircraft, ships, railroad equipment, oil

Table IA4: List of Industries in BEA Fixed Asset Table

This table shows the industries in the BEA fixed asset table, and the closest corresponding 2-digit SICs.

INDUSTRY TITLE	BEA CODE	2-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

and gas equipment, nuclear fuel); c) assets that are firm-specific but not necessarily industry-specific (e.g., fabricated metal products, electronic devices, warehouses); d) assets that are both firm-specific and industry-specific (e.g., communication structures and equipment). We designate an asset as industry-specific if the concentration measured as the Herfindal index of the asset (i.e., one if all of the asset is used in one industry; close to zero if the asset is equally split among different industries) is in the top tercile. We designate an asset as firm-specific if the customization measure (design costs in total production costs of the asset) is in the top tercile. After assigning each of the 71 assets in the BEA fixed asset table into one of the four categories, we calculate the (value-weighted) share of an industry's assets that belong to each category. We then match the industries in the BEA fixed asset table with 2-digit SIC industries, as explained above.

Table IA5: 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 belongs to the four categories: non-industry specific and non-firm specific; industry-specific and non-firm specific; non-industry specific and firm-specific; industry-specific and firm-specific.

Variable	mean	p25	p50	p75	s.d.
Transportation cost	0.520	0.378	0.481	0.675	0.199
Depreciation rate	0.245	0.157	0.215	0.323	0.117
Design cost share	0.159	0.145	0.157	0.179	0.028
Industry sales share	0.016	0.002	0.005	0.020	0.022
% non-ind spec, non-firm spec	0.479	0.334	0.530	0.615	0.209
% ind spec, non-firm spec	0.238	0.001	0.096	0.363	0.283
% non-ind spec, firm spec	0.225	0.161	0.219	0.301	0.095
% ind spec, firm spec	0.058	0.001	0.006	0.093	0.099

IA4 Attributes and 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 very perishable (such as restaurants' fresh food inventory, or certain chemicals). The second and third attributes include mobility and standardization/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 2-digit SIC industry.

We measure inventory durability/shelf life using the ratio of inventory purchase to inventory stock for firms in Compustat ("churn rate"), and then take the average churn rate in each industry. When inventory is perishable, most inventory needs to be purchased or produced during the same period, instead of being stocked for future use. Industries with the lowest inventory churn rate (longest shelf life) include construction, furniture stores, department stores, textile mills, and metal mining. Industries with the highest inventory churn rate (shortest shelf life) include agricultural services, restaurants, recreational services, and hotels.

We measure inventory mobility using transportation cost data based on the BEA input-output table, similar to the analysis in Section 3.1. We start by calculating the transportation cost (as a share of total production cost) for each commodity in the input-output table. For each 4-digit input-output table industry (which can be mapped to a 4-digit NAICS industry), we calculate the overall transportation cost of its inputs as the transportation cost of raw materials, and calculate the overall transportation cost of its output as the transportation cost of final goods. We merge the transportation cost of raw materials and final goods into Compustat based on the 4-digit NAICS. We then calculate the transportation cost of inventory in general for firms in each 2-digit SIC industry, weighting by the amount of raw materials and final goods (available in Compustat). Industries with the highest inventory mobility include apparel, electronic manufacturing, and department stores. Industries with the lowest inventory mobility include nonmetallic mining, construction, and coal mining.

We measure inventory standardization/customization using the share of design cost in total cost based on the BEA input-output table, also similar to the analysis in Section 3.1 for PPE. We start by calculating the design cost (as a share of total production cost) for each commodity in the input-output table. For each 4-digit input-output table industry, we calculate the overall design cost share of its inputs as the design cost of raw materials, and calculate the overall design cost share of its output as the design cost share of final goods. We merge the design cost of raw materials and final goods into Compustat based on the 4-digit NAICS. We then calculate the design cost of inventory in general for firms in each 2-digit SIC industry, weighting by the amount of raw materials and final goods (available in Compustat). Industries with the lowest degree of customization include wood products, building material stores, auto dealers, and restaurants. Industries with the highest degree of customization include communications, business services, and water transportation.

Finally, we measure the share of work-in-progress inventory in total inventory for Compustat firms, and take the average for each 2-digit SIC industry.

Table IA6, Panel A, shows industry-level summary statistics of the inventory physical attributes. Table IA6, Panel B, shows the relationship between the physical attributes and average inventory recovery rates in each industry. As in the analysis of PPE recovery rates, we use physical attributes measured in 1997 (using 1997 Input-Ouput tables and Compustat data). Since inventory in certain industries can be fairly perishable (e.g., fresh food inventory of restaurants), it seems durability is a primary issue. When the inventory is perishable, mobility and customization matter less (perishable inventory is difficult to redeploy anyways). When inventory is more durable, 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 unclear like before, as shown in column (2).

Table IA6: 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 BEA input-output flow table and Compustat data in 1997. Panel B shows the relationship between industry-average inventory recovery rate and physical attributes of inventory in the industry.

Panel A. Summary Statistics

Variable	mean	p25	p50	p75	s.d.
Work-in-progress share	0.201	0.049	0.152	0.271	0.197
Churn rate	25.940	7.100	11.910	36.813	32.568
Transportation cost	0.095	0.033	0.053	0.096	0.117
Design cost share	0.074	0.057	0.073	0.085	0.021

Panel B. Relationship with Inventory Recovery Rate

	Inventory Recovery Rate	
	(1)	(2)
Work-in-progress share	-0.218	-0.221
	(0.187)	(0.191)
Churn rate	-0.013***	-0.013***
	(0.003)	(0.004)
Transportation cost	-0.231*	-0.213
	(0.120)	(0.140)
Churn rate × Transportation cost	0.012	0.012
	(0.013)	(0.013)
Design cost share	-3.791*	-3.962*
	(1.878)	(1.984)
Churn rate × Design cost share	0.127***	0.129***
	(0.043)	(0.045)
Industry sales share		0.326
		(0.929)
Constant	0.813***	0.817***
	(0.149)	(0.151)
Obs	45	45
R^2	0.31	0.31

Robust standard errors in parentheses

IA5 Asset Attributes and Recovery Rates of Other Assets

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

IA5.1 Receivables

Receivable recovery rates can be lower than 100% for several main reasons. First, past-due receivables may not get paid in the end. Second, foreign receivables are difficult to recover. Third, government receivables and receivables due from large, concentrated clients (e.g., Walmart) can also be more 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 from Compustat. For foreign receivables, we calculate the share of non-US sales in total sales as a proxy, using Compustat segment data. For government and large-counterparty receivables, we currently do not have a proxy. For the possibility to offset receivables based on payables, we use accounts payables (normalized by book assets) as a proxy. We calculate the average for each 2-digit SIC.

Table IA7, Panel A, shows summary statistics of these attributes. Table IA7, Panel B, shows their relationship with industry-average receivable recovery rate. As predicted, receivable recovery rate is 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 IA7: 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 industry-average receivable recovery rate and receivable attributes in the industry.

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	0.100	0.036	0.106	0.171	0.131
Accounts payable	0.099	0.064	0.092	0.118	0.045
Industry sales share	0.016	0.001	0.005	0.022	0.023

Panel B. Relationship with Receivable Recovery Rate

	Receivable Recovery Rate	
	(1)	(2)
Doubtful receivable share	-0.946***	-0.920**
	(0.349)	(0.356)
Foreign sale share	-0.140*	-0.142*
	(0.076)	(0.076)
Accounts payable	-1.014*	-1.021*
	(0.580)	(0.583)
Industry sales share		0.493
		(0.717)
Constant	0.808***	0.798***
	(0.067)	(0.063)
Obs	47	47
R^2	0.15	0.16

Robust standard errors in parentheses

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 mainly derive value when combined with the business as a going-concern, and generally do not have liquidation value. Intangibles that are identifiable and transferable likely have higher recovery rates. Second, industry specialists comment that transferable intangibles are mostly useful in the same industry, and they are more valuable in industries with higher profitability.

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 ROA (net income normalized by lagged book assets).

Table IA8, Panel A, shows summary statistics of these industry-level attributes. Table IA8, Panel B, shows their relationship with industry-average intangible recovery rate. As predicted, intangible recovery rates are lower in industries with more goodwill and higher in industries with more knowledge capital relative to organizational capital in intangible stock. Intangible recovery rates are also weakly increasing in industry-average ROA. The relationship with industry size is unclear like before.

Table IA8: Industry-Level Attributes of 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 recovery rate and intangible attributes in the industry.

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 sales share	0.016	0.001	0.005	0.022	0.023

Panel B. Relationship with Book Intangible Recovery Rate

	Book Intangible Recovery Rate	
	(1)	(2)
Goodwill share in book intangibles	-0.377*	-0.402
	(0.222)	(0.252)
Knowledge capital share	0.421**	0.456**
	(0.192)	(0.208)
Industry-average ROA	1.202	1.242
	(0.805)	(0.856)
Industry sales share		-0.434
		(0.977)
Constant	0.339**	0.359*
	(0.161)	(0.187)
Obs	47	47
R^2	0.15	0.15

Robust standard errors in parentheses

IA6 Asset Specificity and Markup Cyclicality

In this section, we present results that higher asset specificity also appears to be associated with more countercyclical markups. We use three different measures of firm-level markups. The first one (muM) follows De Loecker, Eeckhout, and Unger (2020) and uses "Cost of Goods Sold" (COGS) for variable costs. The second one (muX) comes from Traina (2018) and Flynn, Gandhi, and Traina (2019), which also includes "Selling, General, and Administrative Expenses" (SG&A) in variable costs. We thank James Traina for sharing his data and code for these markup measures. The third one is sales over operating costs.

Table IA9 shows the results. Panel A uses firm-level liquidation values (including PPE and working capital, normalized by total book assets) constructed in Section 2.4. Panel B instruments firm-level liquidation values using PPE recovery rates and inventory recovery rates predicted by the physical attributes of PPE (Section 3.1) and inventory (Internet Appendix Section IA4). It also uses the fraction of PPE that is firm-specific discussed in Section 3.1. In all cases, we see that on average firm-level markup is not necessarily countercyclical. However, firm-level estimated markups are significantly counter-cyclical when asset specificity is high (liquidation values are low), but pro-cyclical when asset specificity is low (liquidation values are high). The results also hold for large firms only, or controlling for proxies of financial constraints, to make sure liquidation values are not just capturing the impact of financial constraints (Gilchrist, Schoenle, Sim, and Zakrajšek, 2017).

Table IA9: Asset Specificity and Markup Cyclicality

Firm-level regressions where the left-hand-side variable is firm-level markup, measured following De Loecker et al. (2020) in columns (1) to (3), following Traina (2018) and Flynn et al. (2019) in columns (4) to (6), and using sales over operating costs in columns (7) to (9). Output gap is log real GDP minus log potential GDP. Panel A uses firm-level liquidation values (including PPE and working capital), normalized by total book assets. Panel B instruments firm-level liquidation values using PPE recovery rates predicted by the physical attributes of PPE (Section 3.1) in columns (1), (4), and (7), and using inventory recovery rates predicted by the physical attributes of inventory (Internet Appendix Section IA4) in columns (2), (5), and (8). Panel B also uses the fraction of PPE that is firm-specific discussed in Section 3.2 in columns (3), (6), and (9). Firm fixed effects and industry fixed effects are included in Panel A columns (3), (6), and (9), and in Panel B. R^2 does not include fixed effects. Sample period is 1980 to 2016.

Panel A. Basic Results

	Firm-Level Markup								
		muM			*muX*		Sales/Operating Costs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Output gap	-0.65	-2.48**		-0.19	-1.25		-0.67***	-1.73**	
	(0.40)	(1.05)		(0.20)	(0.75)		(0.24)	(0.64)	
Liquidation val		-0.28***	-0.33***		-0.03	-0.02		0.33***	0.44***
		(0.08)	(0.07)		(0.05)	(0.03)		(0.04)	(0.04)
Output gap × Liquidation val		5.84*	3.18**		3.49*	3.00***		3.81**	3.71***
		(2.89)	(1.53)		(1.80)	(1.06)		(1.65)	(1.16)
Fixed effect	N	N	Ind, Year	N	N	Ind, Year	N	N	Ind, Year
Obs	104,442	96,139	95,062	104,688	96,264	95,193	145,446	134,056	132,695
R^2	0.01	0.02	0.02	0.05	0.05	0.01	0.26	0.28	0.08

Standard errors in parentheses, clustered by firm and time

Panel B. Liquidation Value Predicted by Physical Attributes

	Firm-Level Markup								
		muM			*muX*		Sales/Operating Cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Output gap × Liquidation val	9.89**	4.84		10.33***	2.73*		8.58***	3.92**	
	(3.85)	(3.40)		(2.13)	(1.51)		(1.77)	(1.45)	
Output gap × Frac of PPE firm-spec			-1.68			-1.50**			-1.41*
			(1.38)			(0.72)			(0.77)
Fixed effect	Industry, Year								
Obs	95,062	93,930	97,912	95,193	94,061	98,091	132,695	131,446	137,109
R^2			0.01			0.01			0.06

Standard errors in parentheses, clustered by firm and time

We also test the markup response to demand shocks from defense spending, for different levels of asset specfciity, in the industry-level data from Nekarda and Ramey (2011). Table IA10 shows the result for the industry-average markup using Compustat data as above, and using the original markup measure in Nekarda and Ramey (2011). We also generally observe that markup appears more countercyclical when asset specificty is high (liquidation values are low).

Table IA10: Asset Specificity and Markup Response to Defense Spending Shocks

Industry-level annual regressions using data from Nekarda and Ramey (2011). The left-hand-side variable is industry-level markup, which is calculated as the (sales-weighted) industry average of firm-level markup following De Loecker et al. (2020) in columns (1) to (4), industry average of firm-level markup following Traina (2018); Flynn et al. (2019) in columns (5) to (8), and original average markup in Nekarda and Ramey (2011) Table 8 in columns (9) to (12). Liquidation value is the industry-average of firm-level liquidation value (including PPE and working capital, normalized by book assets). We also instrument the industry-average firm liquidation value using PPE recovery rates predicted by the physical attributes of PPE (Section 3.1) in columns (2), (6), and (10), and using inventory recovery rates predicted by the physical attributes of inventory (Internet Appendix Section IA4) in columns (3), (7), and (11). We also use the fraction of PPE that is firm-specific discussed in Section 3.2 in columns (4), (8), and (12). dly is annual growth of industry-level real output, instrumented by industry-level government demand from defense spending. Sample period is 1980 to the end of Nekarda and Ramey (2011) data.

	Markup											
	muM				*muX*				Original			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
dly	0.003*	-0.027***	-0.025***	0.016**	0.000	-0.029***	-0.026***	0.012*	-0.258	0.263	0.214	-0.569
	(0.002)	(0.006)	(0.005)	(0.007)	(0.001)	(0.005)	(0.003)	(0.006)	(0.170)	(0.453)	(0.371)	(0.501)
dly × Ind avg liq val		0.101***	0.095***			0.091***	0.081***			-1.728	-1.577	
		(0.022)	(0.018)			(0.017)	(0.013)			(1.715)	(1.432)	
dly × Frac of PPE firm-spec				-0.052**				-0.047**				1.239
				(0.021)				(0.020)				(1.550)
Liqval IV	N	PPE	Inventory	/	N	PPE	Inventory	/	N	PPE	Inventory	/
Fixed effect	Industry, Year											

Standard errors in parentheses, clustered by industry and time