Bankrupt Innovative Firms*

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We study how innovative firms manage their innovation portfolios after filing for Chapter 11 reorganization using three decades of data. We find that they sell off core (i.e., technologically critical and valuable), rather than peripheral, patents in bankruptcy. The selling pattern is driven almost entirely by firms with strong secured creditor control, and the mechanism is secured creditors exercising their control rights on collateralized patents. Creditor-driven patent sales in bankruptcy have implications for technology diffusion—the sold patents diffuse more slowly under new ownership and are more likely to be purchased by opportunistic patent trolls.

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1. Introduction

The growth of the economy depends on the production, allocation, and exploitation of innovation. However, investment in innovation involves a high degree of uncertainty and risk of failure, which may at times push innovative firms into a state of distress, even when those firms own a substantial number of accumulated innovation assets and possess a large amount of knowledge. The question remains as to what extent these adverse situations impact firms' innovation management, the market for technology, and technology diffusion as a whole.

This paper takes a step forward in understanding the bankruptcy of innovative firms and its implications for technology diffusion. The analysis is guided by two inter-related questions: At the firm-level, are firms able to retain their technologically critical (i.e. core) innovation in bankruptcy reorganizations, and what economic forces drive the reallocation of innovation? Beyond the failing firms themselves, what is the effect of selling innovation by these firms on technology diffusion?

Failing innovative firms often use the bankruptcy system (in particular, Chapter 11 in the US) to reorganize and seek a "fresh start." Ideally, the bankruptcy system should help viable firms resolve temporary distress and emerge without losing their valuable assets and growth options. One would hope that technologically critical innovation remains with the firm while under-exploited innovation is unleashed to the market (Serrano, 2010; Akcigit, Celik, and Greenwood, 2016). In this way, firms can emerge leaner and stronger while under-exploited patents are further developed elsewhere. However, the bankruptcy system may pose substantial challenges to the restructuring process of innovative firms.

One of the central challenges, especially in the past three decades, is the increasing secured creditor control in Chapter 11—often, it is the creditor, not the Bankruptcy Code or the judge, that is deciding on how the restructuring process unfolds (Baird and Rasmussen, 2002; Ayotte and Morrison, 2009). Innovative firms are particularly vulnerable to this challenge. Creditors' goal in bankruptcy is to protect collateral value and to recover debt with certainty. This goal misaligns with the nature of innovative firms—innovation investments are risky, innovation value is option-like, and asset nature is intangible (Acharya and Subramanian, 2009; Brown, Fazzari, and Petersen, 2009). Creditors, with incentives and control rights, thus may exert negative influence on firms' ability to retain the innovation that they are well-suited to exploit. These creditor-driven sales in turn can disrupt firm-innovation match on the market for technology and stifle technology diffusion.

To empirically study the bankruptcy of innovative firms, this paper assembles a novel data set using information from the United States Patent and Trademark Office (USPTO), BankruptcyData.com, and Public Access to Court Electronic Records (PACER). Our data contain thirty years of Chapter 11 filings of US public firms that own patents (innovative firms). We collect detailed information on patent portfolios, patent transactions, and the characteristics and collateralization history of these patents. This data set highlights the active patent reallocation of failed innovative firms seeking to reorganize. We observe that firms sell a substantial portion of their patents immediately after their bankruptcy filing. On average, firms sell off 18% of the patents in their innovation portfolios during bankruptcy reorganization, typically within two quarters after filing.

Our empirical analysis starts with a robust and ubiquitous finding—bankrupt innovative firms are more likely to sell off their core (i.e. technologically critical and valuable to the selling firm), rather than peripheral, patents during Chapter 11 reorganization. We determine core patents using the measure developed and validated in Akcigit, Celik, and Greenwood (2016) and Brav, Jiang, Ma, and Tian (2018). This measure is built on the technological proximity between a patent and the owning firm's core innovation expertise, and core patents are shown to be crucial for firm value. Our patent-level analysis shows that patents in the highest quartile of the core measure are 30% more likely to be sold compared to the baseline selling rate of an average patent. The pattern cannot simply be explained by patent-level characteristics, like redeployability or liquidity, that may influence the selling decision.

This pattern of giving up core innovation in bankruptcy is diametrically opposed to patterns observed in non-distressed firms. Akcigit et al. (2016) and Brav et al. (2018) both show that non-core patents are sold in those cases. Why do bankrupt innovative firms sell off their core patents, the very patents that one would assume could help firms recover?

We first investigate the role of secured creditor control, and begin by testing whether the patent selling pattern differs by the level of secured creditor control. We measure secured creditor control in three ways: the ratio of secured debt to total debt, creditors recontracting in bankruptcy through debtor-in-possession (DIP) financing, and a post-2000 indicator, since the period is shown to be more creditor friendly. We find that selling core patents concentrates in bankrupt firms with stronger secured creditor control. For example, in firms with an above-median secured debt ratio, core patents are 110% more likely to be sold, more than tripling the economic magnitude in the baseline. Core patents are in fact less likely to be sold in cases with weaker creditor control, in parallel with what happens in non-distressed firms. This evidence lends initial support to the creditor control explanation.

Yet, for this economic reasoning to be true, creditors need to own control rights over the core patents. Even though secured creditors obtain significant control in bankruptcy, their ability to directly affect asset sales is typically bounded by their rights against the collateralized assets. In other words, collateralized patents are more vulnerable than other assets to creditor control. Indeed, in bankruptcy, creditors may use a range of strategies to exert pressure on the firm to sell collateralized assets—such as requesting the judge to terminate the debtor's exclusivity period, to lift the automatic stay, or to convert the case to Chapter 7.

We show that the creditor control mechanism is executed through creditors enforcing their control rights on patent collateral. A firm's core patents are more likely to be ex ante pledged as collateral for debt financing. Importantly, a collateralized patent is seven times more likely to be sold by a firm in bankruptcy than by a non-distressed firm, and this selling pattern holds particularly strongly in firms with stronger creditor control. Moreover, the effect of creditor control on the selling of collateralized patents is the strongest when the secured debt recovery is uncertain, that is, neither excessively over-collateralized (i.e., secured debt is safe) nor under-collateralized (i.e. secured debt becomes residual claims). These pieces of evidence combined explain how core patents are sold through secured creditors enforcing collateral rights.

One might wonder whether firms in bankruptcy may have been unproductive in their previous core business and therefore voluntarily change their lines of business—thus, selling core assets simply reflects this course-switching effort. We show evidence that is inconsistent with this argument. First, most of the firms stay in the same industry (at the four-digit SIC level) upon emergence and keep patenting in the same key technology classes. Second, firms that suffer financial but not economic distress (empirically defined in our sample as high leverage and also high ROA) use the bankruptcy system to resolve temporary liquidity and capital structure issues, but are less likely to change the course of operation. Yet, these firms also give up their core patents. Finally, our results are robust when we focus on patents that are produced more recently, which more likely reflect the firms' future direction of innovation.

When patent sales in bankruptcy are driven by secured creditors, as shown thus far, it may help creditors recover their debt but result in firm-innovation mismatch. As a result, the bankrupt firms may underperform in the long-run and the technologies may be underexploited under the new ownership. In the second half of the paper, we test this conjecture by studying the consequences of bankrupt firms selling patents, both on the selling firms themselves and on technology diffusion.

We find that technologies sold in bankruptcy diffuse slowly after selling. Patents sold during bankruptcy experience a sharp decline in year-over-year citations post transaction. However, this does not mean that those sold patents are of poorer quality—in fact, there is a strong and robust increasing trend in the total number of citations before the sale ("up then down"), supporting the interpretation that the sold patents are high-quality "hot" patents that are poorly used after the sale. In contrast, citations made to sold patents outside bankruptcy, including those sold by the bankrupt firms three years before their bankruptcy filing, show distinct pattern—citations decrease under old ownership and improve after reallocation ("down then up"), which is more consistent with a better firm-innovation match.

The declined post-sale citations reflect how creditor-driven innovation reallocation negatively impacts the market for technology. We find that patents sold during bankruptcy are more likely to be purchased by patent trolls than by practicing users, and that these patents are used mainly for litigation rather than production. Second, there is a higher intensity of separation between patents and their inventors for patents sold by bankrupt innovative firms. In other words, human capital and team knowledge are more likely to be separated from patents when sold in bankruptcy.

In terms of the long-term performance of the firm, we provide evidence that when bankrupt firms sell core innovation, secured creditors recover more at the end of bankruptcy process;

and the high recovery rate appears to come at the expense of the firms themselves—selling firms under-perform in the three years after emergence.

This paper connects to the literature on how financial contracting affects corporate policies (Roberts and Sufi, 2009a; Nini, Smith, and Sufi, 2009, 2012), operational flexibility (Benmelech, Kumar, and Rajan, 2019), and innovative activities (Chava et al., 2017; Hochberg et al., 2018; Mann, 2018). We are the first to document how debt contracts affect the patent portfolios of bankrupt innovative firms. The finding that firms sell core patents highlights that creditor rights and patent collateral can be ex post beneficial to the secured creditors but costly to innovative firms and technological diffusion, laying out an important tradeoff in the process of financing innovation (Acharya and Subramanian, 2009; Ederer and Manso, 2011).

Our paper also adds new evidence to the literature on the market for technology and technology diffusion (Gans and Stern, 2010; Arora et al., 2004). The prior literature, focusing mainly on normal times, portrays a well-functioned market for technology (Serrano, 2010; Akcigit et al., 2016; Brav et al., 2018; Figueroa and Serrano, 2019). We add to this literature by providing evidence that bankrupt innovative firms actively participate in innovation transactions and show distinct selling patterns. Our evidence suggests that these transactions stifle optimal reallocation and technology diffusion when financiers exert influence, warranting closer examinations of the interaction between financial markets and the technology market.

Finally, our findings shed light on asset allocations in bankruptcy. Maksimovic and Phillips (1998), Pulvino (1999), Ramey and Shapiro (2001), Gilson et al. (2016), and Bernstein et al. (2019) study challenges that firms face in reallocating assets in bankruptcy. Benmelech and Bergman (2011), Meier and Servaes (2018), and Bernstein et al. (2018) show that reallocation decisions not only affect the bankrupt firms but also spill over to other firms. Our paper contributes to this literature in two ways. First, our study focuses on the reallocation of patents, which is a growing class of firm assets. Second, we highlight the role of creditors, while the existing literature mainly focuses on asset trading frictions arising from industry condition or market thickness.

2. Data

This section discusses data construction and documents basic selling patterns of patents by bankrupt innovative firms.

2.1. The Sample of Bankrupt Firms

Distressed and insolvent firms file for Chapter 11 in the US to reorganize under bankruptcy court protection. We retrieve all Chapter 11 bankruptcies filed by US public firms from 1981 to 2012 from New Generation Research's Bankruptcydata.com. The sample firms are manually matched with Compustat using firm names and company information, and we remove firms that do not have a valid identifier in Compustat. This initial screening results in 2,169 Chapter 11 cases. We remove cases that were dismissed or pending (151 cases), were merged into another leading case (2 cases), or had unknown outcomes (158 cases). We also remove financial firms (161 cases), which are less relevant in a study of innovation. We then exclude cases with unavailable or incomplete dockets from Public Access to Court Electronic Records, i.e., PACER (74 cases). This process leaves us with a sample of 1,623 cases, including both large mature corporations and entrepreneurial companies that just went public.[1]

We collect key information on the timeline and characteristics of the bankruptcy case from Bankruptcydata.com, including the date of Chapter 11 filing, whether the case is prepackaged or prenegotiated, assets at bankruptcy filing, the outcome of reorganization, the confirmation date and effective date of the reorganization or liquidation plan, and the conversion date for those cases converted to Chapter 7.

We use Compustat for financial statement data reported as of the last fiscal year before the bankruptcy filing. The key financial variables that we construct include leverage (debt in current liabilities and long-term debt, scaled by book assets), ROA (return on assets, calculated as the ratio of EBITDA to book assets), and R&D expenses scaled by book assets.

[1] Our data set is the largest bankruptcy data set for US public firms with detailed case information, twice as large as that listed in the widely used UCLA-LoPucki Bankruptcy Research Database, which covers Chapter 11 filings by US public firms with $100 million in assets in constant 1980 dollars for the sample period. The ability to include smaller firms is particularly important because many smaller entrepreneurial firms own many patents.

We resort to Capital IQ (capital structure details section) and last 10-K or 10-Q filings through EDGAR to compile detailed information on firm's debt structure immediately before bankruptcy filing. We manually identify the following debt types: drawn bank revolvers, term loans, secured bonds and notes, capital leases, other secured debt, unsecured bonds and notes, and total debt, and we collect information on their security and seniority status. Secured Debt Ratio is defined as the sum of the outstanding amount of drawn bank revolvers, term loans, secured bonds and notes, capital leases, and other secured debt, scaled by the total debt amount. This variable is only available for the years after 1995 due to availability of 10-K and 10-Q filings on EDGAR. All variables are winsorized at the 1% and 99% levels.

We determine whether a Chapter 11 firm obtains DIP financing and the final approved dollar amount of such financing using court dockets retrieved from PACER. Specifically, we search for key phrases that can help to identify whether the debtor filed a motion on DIP financing and whether a judge approved it.[2] For cases with incomplete dockets, we resort to bankruptcy plans and news in LexisNexis and Factiva for information on DIP financing.

Furthermore, we use whether hedge funds or private equity funds sit on the official unsecured creditors' committee (UCC) to measure the influence of unsecured creditors in the restructuring process.[3] We collect this information from BankruptcyData.com, PACER, and news searches in Factiva and LexisNexis, following Jiang et al. (2012) and Goyal and Wang (2016). This information is available for a large proportion of our sample firms.

2.2. Patent Data and Key Measurements

We construct patent-holding information of each firm using the National Bureau of Economic Research (NBER) patent database and Bhaven Sampat's patent and citation data, both of which are originally extracted from the USPTO. The combined data are linked to the public firm universe using the bridge file provided by NBER, allowing us to establish the full list of patents that a firm owns at each point in time between 1976 and 2012. The database categorizes each patent into one of 430 technology classes based on the underlying

[2] These key phrases include: *debtor-in-possession financing*, *DIP financing*, *post-petition financing*, *secured financing*, *secured lending*, *post-petition finance*, and *secured finance*. See Li and Wang (2016) for a detailed description.

[3] UCC is the committee that is composed of the seven largest unsecured creditors who are willing to represent unsecured creditors.

fundamental feature of the innovation. It also records the number of lifetime citations received by each patent and the sources of those citations, which help identify the level of utilization and the potential users of each patent.

When owners sell their patents, they file patent reassignment documents with the USPTO. The original USPTO patent reassignment database provides information useful for identifying patent transactions: the assignment date; the participating parties, including the transaction assignee ("buyer") and assignor ("seller"); and comments on the reason for the assignment. We merge the raw assignment data with the Harvard Business School inventor database and the USPTO patent database to gather additional information on the original assignees.

We then follow a procedure, similar to that of Brav et al. (2018) and Ma (2020), in which we identify patent transactions from all patent reassignment records from 1976 to 2015. Importantly, the identified patent transactions do not include cases involving an internal patent transfer, either from an inventor to his/her employer or between two firm subsidiaries. This step is crucial for our study because bankrupt firms are more likely to undergo organizational changes during this period. For example, we ensure that such cases as "General Motors Corporation" reassigning its patents to "General Motors Global Technology Operations" are not counted as patent transactions.[4] We follow Mann (2018) to identify patents that are used as collateral and the exact timing of the loan.

2.2.1. Measuring "Core Patents"

The most important patent-level measure in this study captures whether a patent is core or peripheral to its owning firm. The *Core* measure intends to capture the importance of a patent in the owning firm's technology portfolio; thus it is mostly comparable among patents within a firm's own patent portfolio. A patent can be core and valuable to one firm's central business but it may be peripheral and less valuable in other firms' innovation portfolios.

We follow Akcigit et al. (2016), who formalize the distance between a patent p and a firm

[4] We provide a detailed description of the data and methodology in Appendix A2. Graham, Marco, and Myers (2017) provide a detailed discussion on the USPTO patent reassignment records from the perspective of the data administrator. One potential limitation of this database is that recording a transaction in the USPTO is not mandatory. However, both statute and federal regulations provide strong incentives for reporting in order to claim property rights. These incentives to completely report are particularly strong for firms in distress and bankruptcy when clean property rights are crucial.

i's overall technological expertise using a generalized mean of distances between p and each other patent in firm i's patent portfolio. Specifically, we use the following definition:

$$d_t^{\iota}(p,i) = [\frac{1}{\|P_{it}\|} \sum_{p' \in P_{it}} d_{class}(Class_p, Class_{p'})^{\iota}]^{\frac{1}{\iota}}, \tag{1}$$

where P_{it} denotes the patent portfolio of all patents that are owned by firm i in year t ($\|P_{it}\|$ is the size of the portfolio). $\iota \in (0,1]$ is the power of the generalized mean operator. Following the prior literature, we use $\iota = 0.66$ to calculate the primary measure while all the results are both qualitatively and quantitatively similar using other ι parameters.

The key component in the definition, $d_{class}(Class_p, Class_{p'})$, stands for the distance between a patent pair p and p'. The distance operator $d_{class}(X,Y)$, as defined in Akcigit et al. (2016), is the symmetric distance metric between two technology classes, X and Y, and is calculated based on citation patterns of X and Y. Let $\#(X \cap Y)$ denote the number of all patents that cite at least one patent from classes X and Y simultaneously, and $\#(X \cup Y)$ denote the number of all patents that cite at least one patent from class X and/or Y, and

$$d_{class}(X,Y) = 1 - \frac{\#(X \cap Y)}{\#(X \cup Y)}.$$

Intuitively, this measure means that if each patent that cites X also cites Y ($d_{class}(X,Y) = 0$), then X and Y are highly close in their role in the innovation space, and vice versa. $d_{class}(Class_p, Class_{p'})$ in Eq. (1), therefore, is calculated based on the classes of p and p'.

We define $1 - d_t^{\iota}(p,i)$ as the main *Core* measure for each patent p in firm i, and the higher this measure is, the closer the patent is to the firm's core innovation assets. We also create a dummy variable $I(Core)$, which takes value one if the patent is in the top quartile of *Core* among all patents owned by the firm in each year, and zero otherwise. In our empirical analysis, we present results using both the continuous measure and the dummy.

2.2.2. Measuring Patent Quality and Liquidity

We use patent citations to measure the general quality of a patent. Specifically, our measure $\textit{Scaled Citation}_p$ is defined as the number of citations received in the first three years of a patent's life, scaled by the three-year citation of patents from its own vintage and technology class. $I(YoungPatent)_{pt}$, an indicator variable that equals one if the patent was granted within the past six years, captures patent age (Serrano, 2010). $Redeployability_p$ captures the extent to which a patent p is redeployable and valuable to other potential users of the innovation. Specifically, we define patent-level $Redeployability_p$ as one minus self-cite ratio, where self-cite ratio is the share of citations that patent p receives from the follow-on patents issued to the same company within the first three years after being granted. $MFTLiquidity_{pt}$, a patent-year-level variable, is used to capture the annual likelihood that a patent p could be sold in year t in the market for technology. We follow Hochberg et al. (2018) to compute this *MFT Liquidity* measure as the ratio of transacted patents over the patent population in each technology class and issue year, which we can then uniquely map to each patent p at each time point t.

2.3. Active Sales of Patents in Bankruptcy

We merge our sample of 1,623 Chapter 11 filings by US public firms with the USPTO patent database and require each Chapter 11 firm to own at least one patent at the time of bankruptcy filing. The screening results in a final sample of 518 innovative firms. Figure 1 presents the annual distribution of both innovative and non-innovative firms. The figure shows a strong cyclical pattern, with the number of bankruptcy filings of both types of firms reaching high levels during economic recessions such as those in the early 1990s, early 2000s, and 2008-2009. The bankruptcies of innovative firms account for a larger fraction of total filings after year 2000 (36%) than before it (29%).

[Insert Figure 1 Here.]

Before going into any analysis, we describe the sample by characterizing the dynamics of selling patents around bankruptcy. Table 1 presents bankrupt firms' intensity of selling innovation, tabulated based on their Fama-French 12 Industry categorization (Panel A), and based on the year of bankruptcy filing (Panel B). In each panel, we show the total number of Chapter 11 cases, the number of cases filed by innovative firms, the proportion of firms that sold patents during bankruptcy reorganization, and the percentage of patents sold.[5]

[5] The ratio of sold patents is defined as zero for firms that sold no patents.

[Insert Table 1 Here.]

Selling patents during bankruptcy is a surprisingly pervasive phenomenon. Forty percent of firms sell at least one patent in Chapter 11 reorganization, and transacted patents account for 18% of their patent stock. The proportion of firms that sell patents and the percentage of patents transacted has remained at a fairly stable level since the early 1980s. A cross-sectional comparison in Panel A suggests that the intensity of selling patents in bankruptcy varies across industries. Health care, drug, and medical device companies sell their innovation more than any other industries, with 56% of firms conducting such activities and almost 30% of their patent portfolios being sold. But even in the industries that have the lowest patent selling intensities during bankruptcy (Wholesale and Retail, Consumer Non-durables), nearly 25% of firms sell more than 15% of their patent holdings. A time-series analysis in Panel B suggests that patent sale, even though largely overlooked in academic studies, is not a new phenomenon. The proportion of firms that sell patents and the percentage of patents transacted have remained at fairly stable levels since the early 1980s. Sold patents' market value, calculated based on Kogan et al. (2017), add up to nearly 20% of a bankrupt firm's secured debt amount.

We next construct a firm-quarter panel of all US public firms that have at least one granted patent from the USPTO (that is, a firm is included in the sample after its first patent is issued) to examine the selling intensity of bankrupt firms compared to other patent-holding firms and the non-bankrupt periods. We exploit the following model in the same panel sample of firm i and quarter t:

$$Sold_{it} = \sum_{k=-4}^{4} \beta_k \cdot d[t+k]_{it} + \lambda \times Control_{it} + \alpha_i + \alpha_t + \varepsilon_{it}, \tag{2}$$

where $Sold_{ip}$ is a dummy variable indicating whether patent p is sold during bankruptcy reorganization by its owning firm i; α_i and α_t are firm and year fixed effects, respectively, and the independent variables of interest are the set of dummies, $d[t-4], ..., d[t+4]$, indicating whether the firm-quarter observation fits into the $[-4, +4]$ time frame of the bankruptcy event.

[Insert Figure 2 Here.]

The selling pattern is reported in Figure 2. Even though it takes about 16 months for our sample firms to reorganize in Chapter 11, the increase in patent sales concentrates in the first two quarters after the bankruptcy filing, as indicated by the strongest results in $t+1$ and $t+2$, and it decays quickly afterward. Our estimates show that the probability of selling a patent is 9.6% higher than the benchmark (i.e., non-bankrupt firms) in $t+1$. Comparing coefficients for $d(t-1)$ and $d(t+1)$, we find that the probability of selling increases more than sixfold. The F-test suggests that the six-time increase in probability is statistically significant at the 1% level; at the intensive margin, the increase is even more dramatic. Importantly, we do not observe any secular trends before bankruptcy filings in Figure 2.

To shed light on how the selling behavior of patents compares to those of other assets, we compare the dynamics of innovation sales and other asset sales through §363 of the Bankruptcy Code.[6] We manually collect court records for the subsample of firms with electronic dockets available on PACER. After carefully reading thousands of documents on §363 sale motions, orders, and objections, we are able to determine the nature of assets sold in 540 §363 sale transactions by 153 unique firms in our sample. We code each §363 sale as either "innovation" or "no innovation" based on whether patents are listed in the §363 sale orders.

[Insert Figure 3 Here.]

Figure 3 plots two metrics: 1) the total number of §363 sales from the quarter of filing to four quarters after filing and 2) the quarterly ratio of innovation-related §363 sales to total §363 sales. We find a similar timeliness of asset sales in the quarterly number of §363 sale motions. More interestingly, innovation-related sales occur with greater intensity immediately after bankruptcy filings. In the quarter of filing, nearly 60% of §363 sales are innovation-related, but by the fourth quarter after filing, this ratio drops to 17%. Overall, the pattern suggests that patents appear to be front-loaded in asset sales.

[6] In practice, patent sales are conducted through §363 of the Bankruptcy Code, and those sales constitute our main data sample. Anecdotally, well-known, large-scale innovation sales in bankruptcy, such as those of Eastman Kodak and Nortel, were conducted through §363. Appendix A1 provides a detailed discussion of the §363 sale process and economics therein.

3. The Selling of Core Patents

3.1. Summary Statistics

Table 2 Panel A reports summary statistics of the patent-level data set. This data set covers all patents owned by 518 innovative bankrupt firms that have non-missing values of key patent-level variables. The pooled average of *Sold* is 0.083, meaning that 8.3% of all patents owned by a bankrupt firm at filing are sold.[7] The average of $Core$ with parameter $\iota = 0.66$ is 0.444, comparable to earlier studies such as Akcigit et al. (2016). The variable has large cross-sectional variations with a standard deviation of 0.274. Moving from the 25th percentile to the 75th percentile of the variable will increase the measure by more than three times. A similar pattern holds with parameter $\iota = 0.33$. Nearly 18% of patents are collateralized at the time of bankruptcy, comparable to that reported in Mann (2018). Given that $I(Core)$ is constructed to indicate the top quartile of $Core$, the mean scores are at 0.25. About 25% of the patents in the patent portfolio are six years or younger at the time of bankruptcy filing.

The average value of redeployability is 0.783; this suggests that, on average, 78.3% of citations received by a patent are made by other firms, i.e., external citations. The average *MFT Liquidity* of a patent is 0.033, which means that, on average, 3.3% of patents in a technological class are transacted in a specific year. There is also a large cross-sectional variation in this liquidity measure, with standard deviations of around 0.022, and a large jump from the 0.021 at the 25th percentile to 0.039 at the 75th percentile.

[Insert Table 2 Here.]

Panel B of Table 2 describes the 518 innovative bankrupt firms in the sample. About 20% of the cases are prepackaged filings. The bankruptcy cases, on average, stay in the reorganization process for 511 days. The case outcomes are: 13% acquired, 12% converted to Chapter 7, 51% emerged, and 24% liquidated in Chapter 11. Secured debt accounts for 53%

[7] This ratio is different from the 18% reported in Table 1, which is calculated using unweighted firm-level observations.

of total debt, on average.[8] DIP financing in bankruptcy adds another 8% to make the ratio of DIP and secured debt over total debt about 61%. Hedge funds and private equity funds sit on the UCC in 38% of our sample firms.

Our sample firms are large in general, having $973 million in book assets at filing on average and a median value of $94 million. They own, on average, 175 patents at the time of filing for bankruptcy; the median patent holding is 13, suggesting a highly skewed distribution of firm size and patent stock.[9] In addition, a typical firm in our sample experiences negative ROA and carries high leverage at the time of Chapter 11 filing.[10]

3.2. Baseline Results

Our first question asks whether firms are able to retain valuable core innovation in bankruptcy. We approach this question by examining the characteristics of patents firms sell in bankruptcy. The analysis is performed on a patent-level cross-sectional data set. Each observation is a patent p in a bankrupt firm i's patent portfolio in the year of filing. We estimate the following linear probability model:

$$Sold_{ip} = \alpha_i + \beta \cdot Core_{ip} + \lambda \times Control_{ip} + \varepsilon_{ip}. \tag{3}$$

The key explanatory variable is $Core$, for which both the continuous and categorical versions are used. We control for patent characteristics, including *Scaled Citation*$_p$, $I(YoungPatent)_{pt}$, *Redeployability*, *MFTLiquidity*, and firm-specific patent transaction intensities using firm-level fixed effects. Standard errors are clustered at the firm level.

[Insert Table 3 Here.]

[8] Our statistics are in line with those reported by prior studies. For example, Carey and Gordy (2016) report a mean of 48% of the fraction of secured debt in their sample that is based on S&P LossStats and Moody's Ultimate Recovery databases.

[9] The eventually liquidated firms are typically much smaller in size and patent holdings, so the results in the paper are primarily driven by the firms that eventually emerge. The distinction among all the outcomes will be controlled for and explored in the empirical analyses.

[10] In Table A.2 we compare those innovative bankrupt firms with other bankrupt firms. Those firms are very similar to each other in terms of case and firm characteristics. Innovative bankrupt firms are, however, more R&D heavy, more likely to obtain DIP financing, and less likely to be converted from Chapter 11 to Chapter 7 liquidations.

Table 3 presents the regression results of Eq. (3). Column (1) shows that $Core$ is a strong and positive determinant of whether a patent is likely to be reallocated during bankruptcy reorganization. The coefficient of 0.022 translates a change of $Core$ from the 25th percentile to the 75th percentile to a 1 percentage point $(0.022 \times (0.673 - 0.213))$ increase in the probability of selling, which is a 12.2% jump based on the unconditional probability (8.3%). In column (2), we exploit categorized variables by cutting patents into within-firm quartiles based on $Core$ and creating dummy variables to indicate the quartiles. The dummy indicating the lowest quartile is omitted, and this set of patents serves as an effective benchmark. Core (4th Quartile), also denoted as $I(Core)$, dominates the patent-selling decision. Being one of the top-quartile core patents increases the probability of sale by 2.5 percentage points, which is a 30.1% jump based on the unconditional probability.

In column (3), we use a $Core$ measure defined by whether that patent belongs to the top technological class that the firm innovates in, similar to that in Brav et al. (2018). We find that core patents are 1.6 percentage points more likely to be sold, comparable to that in column (2). The analysis introduces additional controls for patent-level characteristics in columns (4) and (5). This is important since without those explicit controls, core patents may be proxying for patent-level fundamentals that could affect the salability. We find that the pattern of selling off core patents remains robust.

In columns (6) and (7), we repeat the analysis using only firms that eventually emerged from the bankruptcy process and that were not prepackaged, respectively. The goal of the emerging-firm analysis is to mitigate the concern that firms that are eventually liquidated may place everything for sale without discretion. The liquidation decision can then bias the estimation. Note that 51% of firms emerged from Chapter 11, but they own more than 85% of patents in the sample due to the fact that most large and innovative firms emerged from bankruptcy reorganization. Similarly, the goal of removing prepackaged bankruptcies is to exclude cases in which asset-selling decisions are made through a prepackaged agreement between the debtor firm and the creditors before the bankruptcy filing. Creditors are typically more willing to work with the bankrupt firm and are thus more lenient in asset sale decisions in these cases. The results are both qualitatively and quantitatively similar to the full sample presented in column (3).

The pattern of selling core innovation presented in Table 3 is in sharp contrast to the evidence from Akcigit et al. (2016) and Brav et al. (2018) that firms sell peripheral (non-core) patents during normal times. In Table A.4, we expand our bankruptcy-only sample to patents owned by all patenting firms between 1981 and 2012. We confirm that core patents are less likely to be sold in normal times, and the pattern of selling core patents holds only during the bankruptcy period.

3.3. Why Do Firms Sell Core Patents?

Why do innovative firms in bankruptcy sell off their core patents, the very patents that one would presume to help them to recover? Our primary hypothesis centers around the effects of secured creditor control in bankruptcy. The view that firms sell core patents due to creditor control is rooted in the incompatibility between debt and innovation assets (Hall and Lerner, 2010; Kerr and Nanda, 2015). Conceptually, Acharya and Subramanian (2009) show that in bankruptcy, secured creditors, who are granted control rights to collateral, prefer to recover debt with certainty through selling innovation assets rather than maximizing the value of the going concern. Alternatively, it is possible that bankrupt firms may have been unproductive in their previous core business operations, and thus selling core patents reflects their course-changing strategy and therefore not the adverse consequence of creditor control.

3.3.1. Heterogeneity Across High vs. Low Creditor Control

We first conduct three sets of subsample analysis using alternative proxies for secured creditor control. Specifically, we run our main specifications separately for firms with high and low creditor control, and test whether the intensity of losing core patents differs in subsample with high vs. low secured creditor control. In addition, we present results in which we interact measures for core patents with the creditor control dummies. To allow full flexibility, we also interact all other control variables with creditor control dummies as well. With this setup, the coefficient for $Core \times High$ (a dummy indicating stronger creditor control) tests whether the pattern of giving up core patents is significantly different in firms with high versus low creditor control.

We adopt three different measures for creditor control. The first measure is *Secured Debt*

Ratio following Carey and Gordy (2016) and Gilson, Hotchkiss, and Osborn (2016). The construction of the variable is detailed in Section 2. Second, we use the sum of the amount of DIP financing and secured debt scaled by total debt, following Skeel (2004), Li and Wang (2016), and Eckbo, Li, and Wang (2019), who show that DIP contracts grant significant control to secured creditors and have become one of the most important governance levers in Chapter 11. In the third set of tests, we divide our Chapter 11 sample by the turn of the century and make intertemporal comparisons. This intertemporal division is motivated by two sets of studies. First, the Chapter 11 system has become more creditor friendly since the late 1990s (Baird and Rasmussen, 2002; Roberts and Sufi, 2009b; Bharath et al., 2014). Second, major update to Article 9 of the Uniform Commercial Code in 2001 and state adoptions afterward help firms better deal with security interests in intangible assets and ease the way for secured creditors to foreclose on collateral in case of default (Mann, 2018).

[Insert Table 4 Here.]

In Panel A of Table 4, we perform the main specification on subsamples categorized by above-median versus below-median value of secured debt ratio. The pattern of selling core patents is almost purely driven by firms with strong creditor control. The coefficient estimates for $Core$ and $I(Core)$ in the subsample of firms with high secured debt ratios are statistically significant and more than double in magnitude compared to those presented in the baseline regressions in Table 3. In contrast, in firms with low secured debt ratios, the selling probability is either independent of, or negatively related to, a patent being core. The positive interaction terms in columns (3) and (6) are large and statistically significant at the 1% level, consistent with the estimates from the subsample tests. Column (6) provides an easy interpretation of the economic magnitude—a core patent is 8.1 percentage points more likely to be sold if the secured debt ratio is high.[11] The same pattern holds in Panel B when we use DIP financing in bankruptcy as a source of creditor control in addition to the pre-petition secured debt discussed above.

In the third set of tests, presented in Panel C, we show that creditor influence in selling

[11] To partially mitigate the concern that firms with high levels of secured debt are different than those with low levels of secured debt, in Appendix Table A.5 we show that firms with high vs. low levels of secured debt are observably similar to each other.

core patents is an important concern from the 2000s to the present. In contrast, firms that filed for Chapter 11 before 2000 are not more likely, and even are less likely, to sell core innovation. This evidence complements that presented in Panels A and B, showing that creditor influence in selling core patents is an important concern in the present.

3.3.2. Mechanism: Patent Collateralization

Evidence in Table 4 provides initial support to an interpretation that secured creditors drive bankrupt firms to sell off core patents. However, to identify the role of creditor control in selling innovation, we need exogeneous variation to bankruptcy filing decisions or to creditor rights in bankruptcy. Without the fortune of having such a setting, we further our analysis with an arguably more direct approach. We establish the impact of creditor control through exploring a mechanism that is unique to secured creditors—patent collateral and the enforcement of rights on collateralized assets in bankruptcy.

For the collateral mechanism to drive the sell-off of core patents, the economic reasoning needs to be supported in several key steps: core patents must be collateralized ex ante for credit; creditors enforce their rights on collateral ex post; and moreover, strong secured creditors are more likely to do so.

We first investigate whether core patents are more likely to be collateralized. In Table 5 Panel A, we perform a patent-level regression similar to that in Mann (2018), in which each observation is a USPTO-granted patent. We focus on the $Core$ measure, which is measured at the granting year. The outcome variable is a dummy indicating whether an individual patent is ever pledged as collateral. We find that, as hypothesized, core patents are much more likely to be used ex ante as collateral for debt financing. In fact, the economic magnitude is large—for example, in column (4), the coefficient of $I(Core)$ suggests that core patents are 7 percentage points more likely to be used as collateral, which is a 45.2% increase of the unconditional probability that a patent is used as collateral (15.5%). We also show that patents of higher quality and patents that are more redeployable to other users are more likely to be collateralized, in line with several recent studies (Hochberg, Serrano, and Ziedonis, 2018; Mann, 2018).

[Insert Table 5 Here.]

Second, we examine whether secured creditors enforce their rights specifically on the pledged collateral. We construct a sample at the patent-year level of all patents owned by a firm that eventually filed for Chapter 11 bankruptcy. We investigate whether, during the bankruptcy reorganization process, the collateralized innovation is more likely to be sold. We regress an indicator that a patent is sold in the year on whether the patent is collateralized ($I(Collateralized)$), whether the owning firm is going through bankruptcy reorganization in that year ($I(In\ Bankruptcy)$), and the interaction of the terms.

Table 5 Panel B presents the results. In column (1), the negative coefficient of $I(Collateralized)$ shows that collateralized patents are not more likely to be sold outside bankruptcy. This is sensible since—as shown in Panel A—collateralized patents are often core assets of the firm. The key term, $I(Collateralized) \times I(In\ Bankruptcy)$, carries a positive coefficient, showing that collateralized patents are 7.1 percentage points more likely to be sold in bankruptcy than outside bankruptcy. Column (2) shows similar results. The evidence is consistent with the fact that lenders' foreclosure rights are only exercised upon payment defaults, which are triggered by the bankruptcy filing.

Third, we confirm that sales of collateralized patents concentrate in bankrupt firms with stronger creditor control. In Table 5 Panel C, we use the sample of patents owned by bankrupt firms and follow the design and measurements of Table 4. We show that collateralized patents are indeed more likely to be sold, particularly in firms with strong creditor control. Combining this evidence with the fact that core patents are ex ante more likely to be used as collateral, our results show that the secured creditors' incentive to recover their claims together with their lien rights prompt the bankrupt firm to sacrifice collateralized and yet strategically important patents.

3.3.3. Level of Collateralization

To further isolate the influence of creditor control on selling collateralized innovation, we make use of the information on the level of collateralization of secured creditors. Notably, secured creditors' incentives to enforce fast sales of collateralized patents depend on the extent of collateralization of secured debt. As suggested by Ayotte and Morrison (2009), when secured creditors are slightly over-secured, they tend to favor fast resolution through asset sales. In contrast, their preferences for quick sales are weakened when they are under-secured (so secured debts become residual claims) or substantially over-secured (so secured debts are almost certainly safe), in which case their payoffs are hardly affected by whether the collateral is sold or not. We use the ratio of total secured debt amount to the book value of assets as a proxy for the level of collateralization to perform subsample tests.

[Insert Table 6 Here.]

In Table 6, we find that the selling of core innovation is less pronounced for the subsample of firms with under-collateralized or substantially over-collateralized secured debt. However, as a caveat, our results should be interpreted with caution, as a secured debt's lien is not always on all assets of the debtor firm. The combined evidence shows that bankrupt innovative firms give up their core innovation due to secured creditors exercising their rights on the collateralized patents in bankruptcy.[12]

3.3.4. Do Bankrupt Firms Sell Core Patents to Switch Business?

Compared to healthy firms, firms in bankruptcy may have been unproductive in their previously core business operations, and they may voluntarily want to change their line of business. As a result, selling core assets may simply reflect this course-changing strategy and in this sense be mechanical. We provide suggestive evidence below that is inconsistent with this alternative explanation.

To start, among all firms for which we could track the industry categorization post-bankruptcy, we find that more than 90% of the them stay in the same primary four-digit SIC categorization upon emergence and keep patenting in the same key technology classes.

[12]To investigate whether the selling of core patents can be mitigated by the presence of specialized distressed investors as large unsecured creditors, who are typically the new residual claimants of firm value at emergence and have strong incentives to prevent the sale of strategically important assets, we perform our main specification on subsamples categorized by whether hedge funds and private equity funds are members of the unsecured creditors' committee (UCC) (Hotchkiss and Mooradian, 1998; Jiang et al., 2012; Ivashina et al., 2016; Waldock, 2017). Table A.6 shows that the selling of core patents is stronger when no such specialized investors are on the UCC. The behavior of selling core patents is not pronounced in the subsample of firms with a presence of strong unsecured creditors. The evidence is consistent with the fact that the secured creditors' agenda for pushing patent sales is more likely to be uninterrupted when there are dispersed unsecured creditors in place.

Second, we show that even among firms and patents that are most economically viable and therefore are least likely to want to switch course, the pattern of selling core patents remains robust. We focus on firms that appear to suffer financial but not economic distress, empirically defined in our sample as top-tercile leverage with top-tercile ROA (Asquith et al., 1994; Andrade and Kaplan, 1998). These firms typically use the bankruptcy system to resolve temporary liquidity and capital structure issues, and they are less likely to change their business. We find that these firms also lose their core patents, as shown in column (8) of Table 3.

Third, our result also holds when we focus on patents that are produced more recently. If a firm is on the path of changing its main business due to poor operational performance, one would expect to see that it keeps close hold of core patents recently developed since recent patents are more likely to reflect the future direction. In column (9) of Table 3 we show that even among the most recent patents, the pattern of selling core patents remains robust.

Overall, the evidence is inconsistent with the explanation that the bankrupt firms are actively changing business focus. Admittedly, it is inherently difficult to cleanly uncover firms' strategies. In the section to follow, even though the analysis aims at broadening our focus to the market for technology and technology diffusion, several analyses can be tied back to this "course-changing" concern and provide further evidence to strengthen our argument against it.

4. Market for Technology and Technology Diffusion

The previous section shows that creditor-driven patent sales are of great size, immediate, and in directions that are different from normal firms. This creates an important set of questions for us to explore through the lens of the market for technology and technology diffusion—Are patents sold by bankrupt firms allocated to the right buyers? How are sold patents used under the new ownership? Do selling firms retain inventors after patents are reallocated? Answers to these questions will help better understand the implications of patent reallocation in bankruptcy and the functioning of the market for technology in facilitating technology diffusion.

4.1. Post-sale Citations

We first characterize the citation dynamics of patents sold. Figure 4 plots the coefficients β_k from the following regression at the patent (p)-year (t) level:

$$Citation_{pt} = \sum_{k=-3}^{+3} \beta_k \cdot d[t+k]_{pt} + \gamma \cdot Controls_{pt} + \alpha_p + \alpha_t + \varepsilon_{pt}. \tag{4}$$

$Citation_{pt}$ is the number of new citations a patent receives in a given year. One can think of this annual citation flow measuring the exploitation of the underlying technologies defined by the patent. The dummy variable $d[t+k]$ equals one if the patent observation is k years from the sale of the patent, and zero otherwise. We control for patent age, measured as the logarithm of the patent age in year t. We also include year and patent fixed effects, α_t and α_p. The β coefficients thus capture the citation dynamics of sold patents around the transaction compared to the universe of all other patents.

Using this regression framework, we perform multiple regressions that are shown in Figure 4. Those analyses differ in two dimensions. First, we separately characterize the citation dynamics of patents sold by different firms and in different periods—sold in bankruptcy (Panel A), outside bankruptcy by non-bankrupt firms (Panel B), and by bankrupt firms but sold three years prior to bankrupty filings (Panel C). Second, for the $Citation_{pt}$ variable for each patent-year, we perform separate estimations using the total citations received by the patent, those from the buyer, and those from the seller (i.e., the bankrupt firm itself for in-bankruptcy sales) .

[Insert Figure 4 Here.]

Several interesting findings emerge. First, the overall utilization of the patents sold during the bankruptcy process experiences an "up then down" dynamic (A1). In contrast, for sales that happen out of bankruptcy, patent citations experience a clear increase post sales following a decline beforehand, i.e., "down then up" (B1). The magnitude is economically meaningful. In A1, the -0.075 at $[t+3]$ translate to a 14% decrease of annual citations. The pattern suggests that for those sales outside bankruptcy, patents are typically better matched to the buyer and thus are better exploited (see B2 for buyer citations), consistent with the argument in Akcigit et al. (2016). Bankrupt firms, on the other hand, sell better-utilized hot patents (the "up" part), yet they fall in total citations afterward (the "down" part). This means that those patents do not necessarily better fit the buyer or are better exploited (see A2).

Second, the number of citations made by the bankrupt firm remains flat prior to and subsequent to patent sales in bankruptcy—the post-sale usage pattern is statistically indistinguishable from that prior to the sale. Out-of-bankruptcy sales feature a sharp decline in internal usage before sale (B3), which partially contributes to the pre-sale decline of total citations in B1. The evidence suggests that the firms sell under-exploited patents out of bankruptcy.

Finally, one may wonder whether healthy firms, as used in Panel B, are not a good benchmark group to compare to bankrupt firms. We share this concern and use Panel C to analyze an alternative benchmark—bankrupt firms themselves, but three years prior to bankruptcy. Across all three measures of citations, the patterns are very close, both qualitatively and quantitatively, to those shown in Panel B.

Put together, the post-sale citation dynamics suggest that out of bankruptcy, firms sell under-exploited patents and the patents appear to be better exploited post sale. In-bankruptcy sales, however, feature the transfer of better-used patents that ex post become less impactful in the hands of the new owners.

4.2. Patent Troll Purchases and Patent Litigation

We next examine the types of buyers of the patents sold in bankruptcy, with a specific focus on the role of patent trolls. Patent trolls are becoming an important concern for innovation (Cohen, Gurun, and Kominers, 2016). They purchase patents with the purpose of bringing lawsuits against cash-rich innovative firms, and they do so in an opportunistic manner. If the reallocation of patents in bankruptcy is mainly for the redeployment of technologies, those patents should be sold to the potential users of the technologies, i.e., the practicing entities. If, however, the sale of core innovation is a result of creditors' push for a quick sale of collateral, opportunistic patent trolls can be more active buyers in this process.

We start by investigating whether patents sold in bankruptcy are more likely to be sold to a patent troll. We construct a cross-sectional data set of all patent transactions between 1981 and 2015, and we regress the indicator of whether it is sold to a patent troll on the dummy of whether the sale happens in bankruptcy, where the patent troll indicator is obtained from Akcigit et al. (2016) and Cohen, Gurun, and Kominers (2018). The results are shown in Table 7 Panel A. We find that patents sold in bankruptcy are more likely to go to a patent troll. In terms of economic magnitude, the 0.020 in column (4) means that in-bankruptcy sales are 200% more likely to be sold to a non-practicing entity than are out-of-bankruptcy sales (baseline rate of patent troll purchases is 1%).

[Insert Table 7 Here.]

Since patent trolls focus on the promise of litigating using patents rather than exploiting the technologies, we would see that core patents in categories with high litigation risk are more likely to be bought. To capture a patent's litigation risk, we obtain data from Lex Machina, Derwent LitAlert, and the RPX database. We calculate the litigation risk of each technology class as the ratio of litigated patents over the total number of patents in the technology class. Table 7 Panel B presents the results, structured similarly as above, showing that the pattern of selling core innovation is associated with the potential of litigating using purchased patents. Even though patent litigation is uncommon in our sample (1% of patents are in litigation), it has strong explanatory power in patent allocation in bankruptcy. Overall, this evidence shows that patents sold in bankruptcy are more likely to go to patent trolls for litigation reasons than to be used in productive exploitation.

4.3. The Separation of Patents and Inventors

Last, we seek evidence from the reallocation of inventors associated with sold patents. Inventors possess patent-specific human capital that is hard to replace, making inventors particularly valuable if the firm wants to keep inventing in the same class (Jaravel, Petkova, and Bell, 2018). Outside of bankruptcy, inventors of sold patents leave the firm with a much higher intensity, reflecting the sellers' intention to stop exploiting the technologies when selling them and buyers' intention to acquire human capital together with the patents (Brav et al., 2018).

[Insert Table 8 Here.]

Table 8 investigates inventor mobility around corporate bankruptcy. The key indicator variable is whether an inventor leaves the company in the next three or five years. Consistent with earlier research, inventors are more likely to leave when their patents are sold, often moving to the buyer to avoid the separation of human capital with innovation. Interestingly, the interactions term of the bankruptcy dummy and patent sale dummy is negative and economically sizable. This means that patent transactions during bankruptcy are not accompanied by inventor mobility. In other words, human capital and team knowledge are more likely to be separated from the patents when sold in bankruptcy. This finding is consistent with the prior evidence that many of the buyers are non-practicing entities and do not maintain human capital. This separation of human capital and innovation can also explain the slow-down in technology diffusion, and suggests even bigger losses than those reflected in the citation dynamic. Finally, the evidence also suggests that bankrupt innovative firms attempt to maintain the continuity of innovation through maintaining human capital.[13]

4.4. Effects on the Innovative Firms

One may be tempted to conclude from the evidence presented in this paper that empowering creditors in bankruptcy is detrimental to innovation. However, the economics issue of optimal creditor rights and innovation policy is complicated.

On the one hand, as shown in our paper, bankrupt firms give up core innovation under strong creditor control, which may be costly to the long-term growth of the bankrupt firm. One way to show this is to ask how creditors fare at the cost of the bankrupt firm. Following prior studies that examine post-emergence performance of bankrupt firms (Hotchkiss, 1995; Kalay et al., 2007), we examine how the recovery of secured creditors and the performance of the subset of emerging firms vary by the fraction of core innovation sold. In Table 9, we show that secured creditors recover more at the end of the bankruptcy process, but firms under-perform in the three years after emergence when the firms sell (core) innovation in

[13] In untabulated results, we find that inventors are even less likely to leave the bankrupt firms if these firms adopt Key Employee Retention Plans to maintain key employees from departing.

bankruptcy.[14] This ex post cost might discourage ex ante investments in innovation with the hope of avoiding distressed states. The argument is in line with earlier findings such as Acharya and Subramanian (2009), who show that countries that have strong creditor rights witness lower rates of patenting.

[Insert Table 9 Here.]

On the other hand, a different school of thought suggests that strong creditor rights may have positive ex ante effects on innovation by facilitating the financing of innovation. Hochberg et al. (2018) and Mann (2018) both find that patents are widely used as collateral, which enables the relaxation of financial constraints for innovative firms. Access to debt finance in turn allows these firms to make more investments in R&D (Chava, Nanda, and Xiao, 2017; Farre-Mensa, Hegde, and Ljungqvist, 2017), and thus strengthening creditor rights appears to foster innovation.

Indeed, the goal of this paper is to highlight the ex post outcome of creditor control for innovative firms by providing a detailed study of innovation sales in the bankruptcy restructuring process. Designing the optimal debt contract to facilitate innovation in and out of bankruptcy is difficult and beyond the scope of the paper. But our evidence does suggest that the consequence of innovation reallocation under strong creditor control should be an important consideration in related discussions. Those reallocations not only relate to firm performance, but also the preservation and adoption of valuable innovation for the economy.

5. Concluding Remarks

This paper provides a comprehensive study on bankrupt innovative firms that seek "a fresh start" using Chapter 11. Those firms sell, almost immediately, their core innovation (i.e., technologically critical to the business) instead of peripheral innovation. They give up their core innovation due to creditor control through the collateral mechanism. We also document the negative consequences of such patent reallocations to the firms themselves and to technology diffusion.

[14] To perform this analysis, ideally we would need to observe firm performance independent of bankruptcy outcomes; but the reality is that the financial performance can be observed for only those firms that report to the SEC after emergence from bankruptcy. This explains the small number of observations.

These findings have several implications that may be worth highlighting. First, in the recent debate over bankruptcy code reform (such as that from the American Bankruptcy Institute Commission to Study the Reform of Chapter 11 in 2015), for a knowledge-based economy, it may be important to consider the impact on innovation (mis)allocation and technology diffusion. Second, from a firm's perspective, the optimal financial contracting with investors should factor in the ex post cost to innovation. Third, this paper raises, but does not fully answer, the question of how to efficiently redeploy and aggregate innovation from firms that go bust. As many firms, including innovative firms, are negatively affected by the COVID-19 pandemic, this paper provides evidence useful for the discussion on preserving innovation ability and maintaining the viability of innovative firms, which is becoming a burgeoning concern of practitioners and policy makers.

Key Variable Definitions

Variable	Definition and Construction
	a. Patent-level Characteristics
Core	Calculated as the generalized mean between the patent and the whole patent portfolio owned by the firm, following Akcigit, Celik, and Greenwood (2016).
I(Core)	Equals one if a patent is in the top quartile of $Core$.
MFT Liquidity	A patent-year level variable, calculated as the ratio of transacted patents in the patent's technology class over the patent stock in that class.
Redeployability	Proxy for the degree to which the value of a patent is redeployable by other firms—measured as the share of citations to that patent within three years that are made by other firms (i.e., non-self citations).
I(Young Patent)	Equals one if the patent is granted no earlier than six years prior.
Scaled Citations	Citations received in the first three years of a patent's life scaled by this three-year citation of patents from its own vintage and technology class.
Collateral	An indicator variable that takes a value of one if a patent is used as collateral for financing.
Litigation Risk	The ratio of litigated patents in a certain USPTO technology class.
	b. Bankruptcy Case Characteristics
Prepack	An indicator variable that takes a value of one if a bankruptcy is prepackaged or prenegotiated. According to the definition by LoPucki UCLA database, a case is prepackaged if the debtor drafted the plan, submitted it to a vote of the impaired classes, and claimed to have obtained the acceptance necessary for consensual confirmation before filing. On the other hand, if the debtor negotiates the plan with fewer than all groups or obtains the acceptance of fewer than all groups necessary to confirm before the bankruptcy case is filed, then the case is regarded as prenegotiated.
Duration	Number of days in bankruptcy, from the date of filing to the date of plan confirmation.
Secured Debt Ratio	The fraction of secured debt in total debt of the bankrupt firm. Secured Debt Ratio is defined as the sum of outstanding amount of drawn bank revolvers, term loans, secured bonds and notes, capital leases, and other secured debt, scaled by the total debt amount.
(DIP + Secured Debt)/Total Debt	The dollar amount of debtor-in-possession (DIP) financing plus secured debt, scaled by total debt. The DIP value is zero for those firms that do not obtain DIP financing.
HF/PE on UCC	An indicator variable that takes a value of one if at least one hedge fund or private equity fund sits on official unsecured creditors' committee (UCC)
Collateralization Ratio	The ratio of secured debt to book assets.

Financial Distress	An indicator variable that takes a value of one if the bankrupt firm experiences financial (but not economic) distress, which is defined as firms in the top tercile in ROA and the top tercile in leverage in our sample firms.
	c. Firm Characteristics
Assets	Total book assets in millions, adjusted to 2007 US dollars.
Leverage	Book debt value scaled by total assets.
Sales growth	The growth of net sales from t to t-1.
ROA	Earnings before interest, taxes, depreciation, and amortization scaled by total assets.
R&D/Assets	Research and development expenses scaled by total assets.

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Figure 1. Number of Bankruptcy Cases of Innovative Firms

This figure presents the number of bankruptcy cases of US public firms in each year. We retrieve all Chapter 11 bankruptcies filed by US public firms from 1981 to 2012 from New Generation Research's Bankruptcydata.com. The sample firms are manually matched with Compustat using firm names and company information, and we remove firms that do not have a valid identifier in Compustat. We remove cases that were dismissed, were pending as of mid-2016, were merged into another leading case, and had unknown outcomes. We also remove financial firms, which are less relevant in a study of innovation. We then exclude cases with unavailable or incomplete dockets from Public Access to Court Electronic Records, i.e., PACER. This process leaves us with a sample of 1,623 cases. We separately report cases of innovative firms and non-innovative firms, and a firm is categorized as innovative if it owns at least one successfully granted USPTO patent at the time of bankruptcy filing.

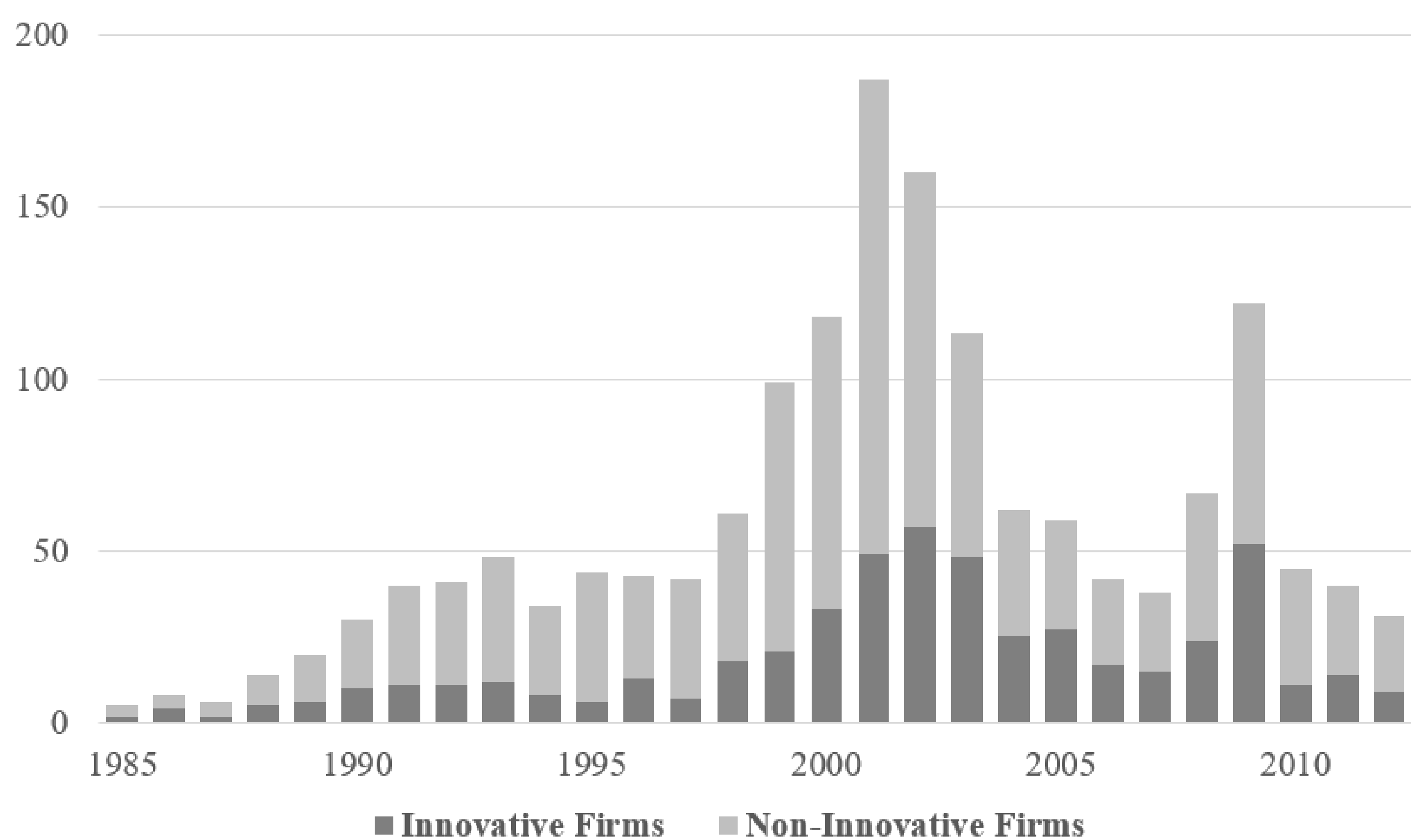
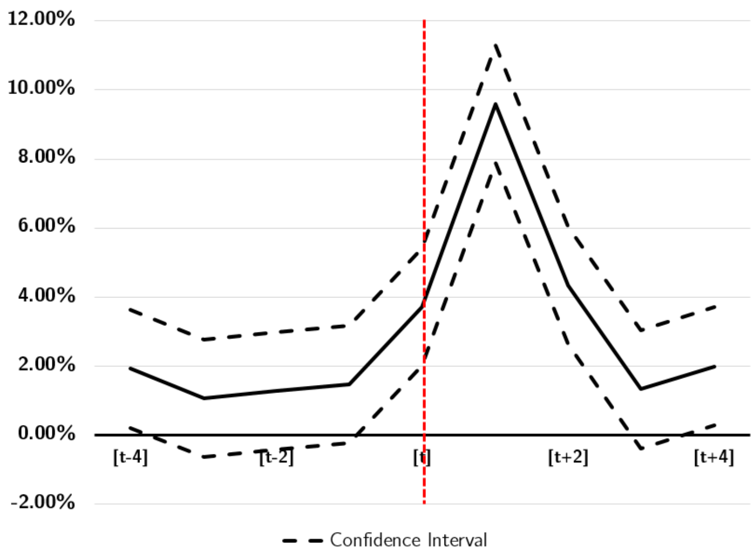


Figure 2. Selling Patents around Bankruptcy Filings

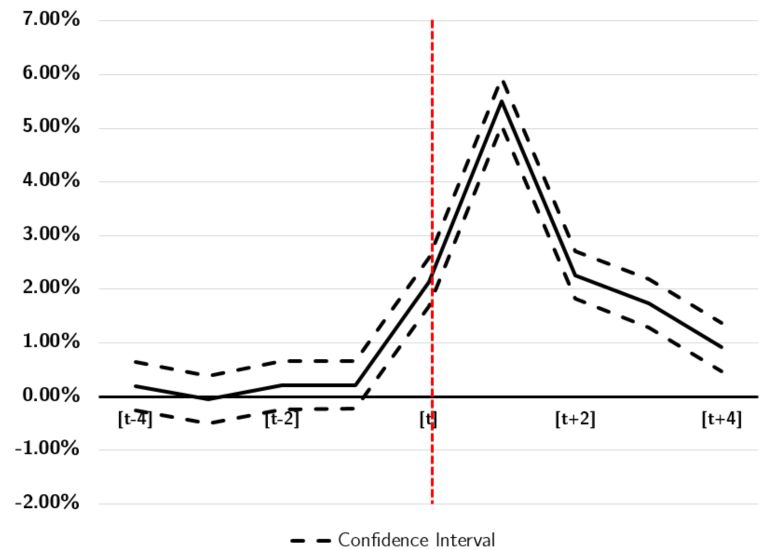
This figure presents the dynamics of the intensity of selling innovation from four quarters before the filing of bankruptcy to four quarters after the filing. We perform the analysis on a firm-quarter panel of all US public firms that have at least one valid patent grant from the USPTO (that is, a firm is included into the sample after its first patent is issued). Dependent variables are the dummy variable indicating whether the firm sold any patents in that quarter (Panel (a)) and the ratio (can be 0) of patents sold over the size of the firm's patent stock as of the beginning of the quarter (Panel (b)). The coefficients and 95% confidence intervals are estimated from the following specification:

$$Selling_{it} = \sum_{k=-4}^{4} \beta_k \; d[t+k] + \lambda \times Control_{it} + \alpha_i + \alpha_t + \varepsilon_{it}.$$

Independent variables of interest are the set of dummies, $d[t-4], ..., d[t+4]$, indicating whether the firm-quarter observation fits into the $[-4, +4]$ time frame of the bankruptcy event. We plot the β_k coefficients, which are the estimates representing the differences in trends in selling between bankrupt firms and the benchmark of public firms. We include both firm and year fixed effects in the estimation to absorb time-invariant selling intensity at the firm level, as well as time trends in the market for innovation. Standard errors are clustered at the firm level.



(a) **Probability of Selling Innovation**



(b) **Ratio of Innovation Sold (%)**

Figure 3. Innovation-Related Sales in §363 Asset Sales

This figure plots both the total number of §363 sales from the quarter of filing to four quarters after the filing, and the quarterly ratio of innovation-related §363 sales to total §363 sales. §363 sales cases are manually collected from US court records, and each of the collected §363 sales is coded as "innovation" or "no innovation" based on asset descriptions in the motion of sales and order of sales. We are able to determine the nature of assets sold in 540 §363 sale transactions by 153 unique firms in our sample. The percentage of sales with innovation is presented in bars, and the total number of sales is presented in dots.

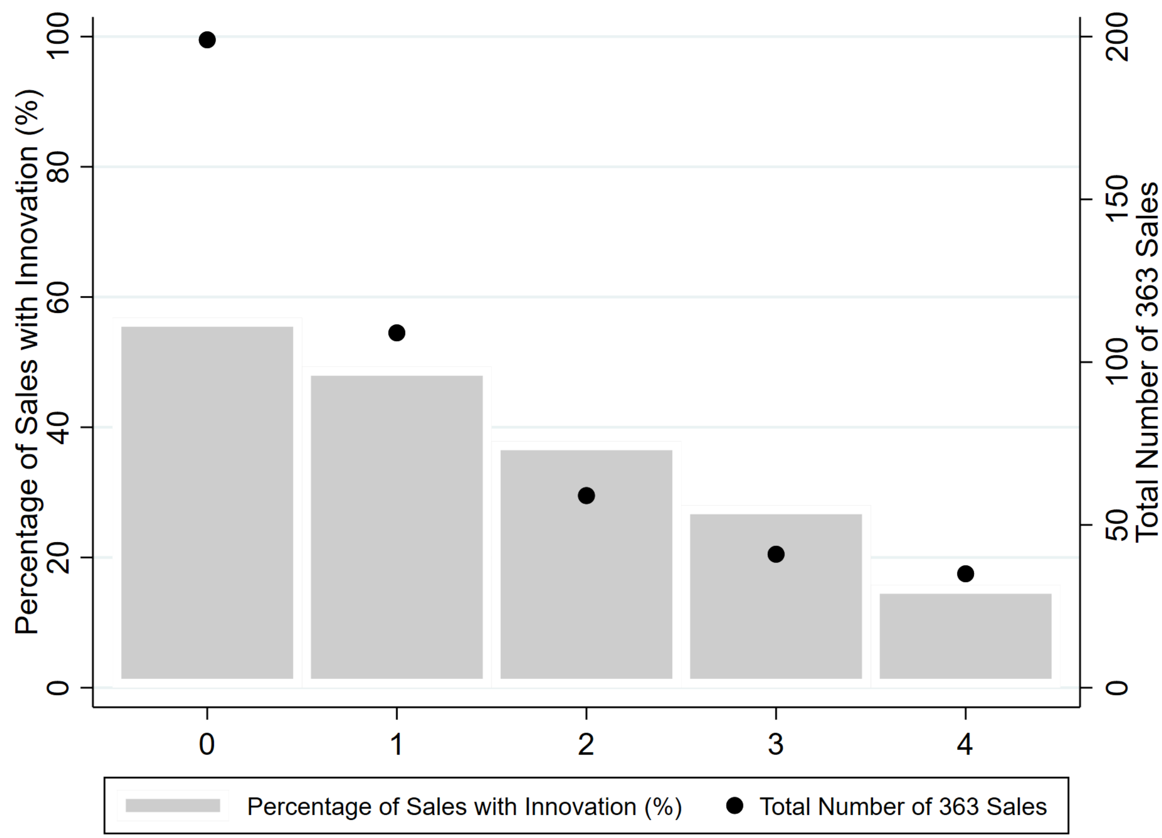


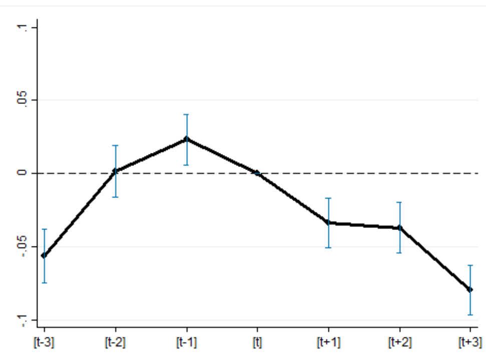
Figure 4. Citation Dynamics around Patent Transactions of Bankrupt Firms

This figure plots the coefficients β_k from the following regression at the patent (p)-year (t) level:

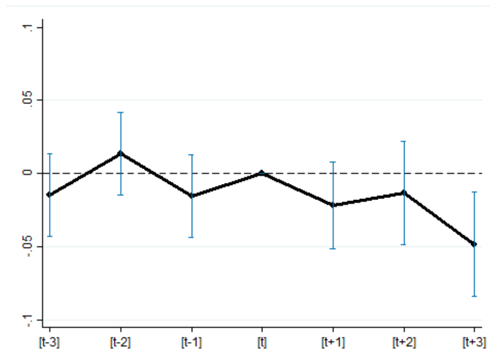
$$Citation_{pt} = \sum_{k=-3}^{+3} \beta_k \cdot d[t+k]_{pt} + \gamma \cdot Controls_{pt} + \alpha_p + \alpha_t + \varepsilon_{pt}.$$

$Citation_{pt}$ is the number of new citations a patent receives in a given year, and we separately estimate using the total citations received by the patent, those received from the buyer, and those received from the seller that originally owned the patent prior to the sale. We also separately estimate for patent sales in and out of bankruptcy. The figure caption labels the source of citations and the patent sales sample for the figure. The dummy variable $d[t+k]$ is equal to one if the patent observation is k years from the sale of the patent, and zero otherwise. We control for patent age, measured as the logarithm of the patent age in year t. We also include year and patent fixed effects, α_t and α_p. Standard errors are clustered at the patent level.

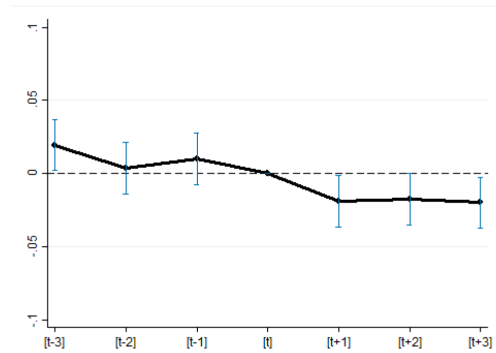
Panel A: Patent Transactions in Bankruptcy



(A1) Total citation to sold patents

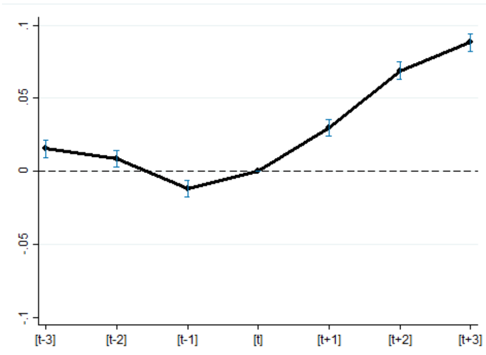


(A2) Buyer citation to sold patents

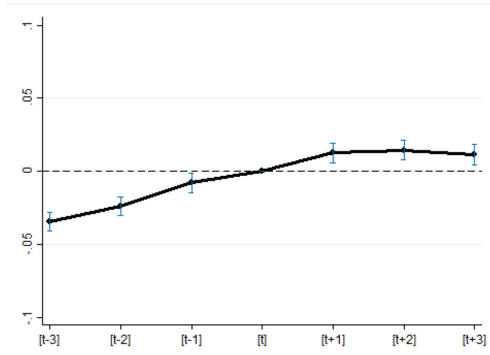


(A3) Seller citation to sold patents

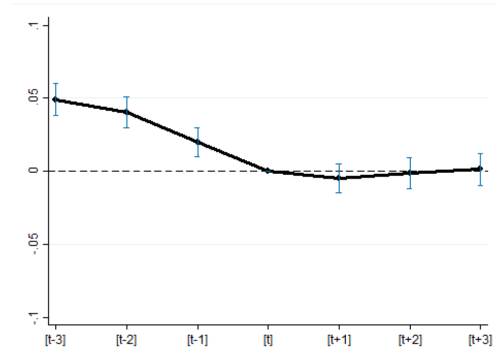
Panel B: Patent Transactions By Healthy Firms



(B1) Total citation to sold patents

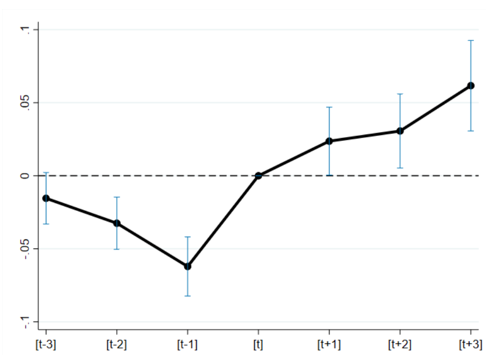


(B2) Buyer citation to sold patents

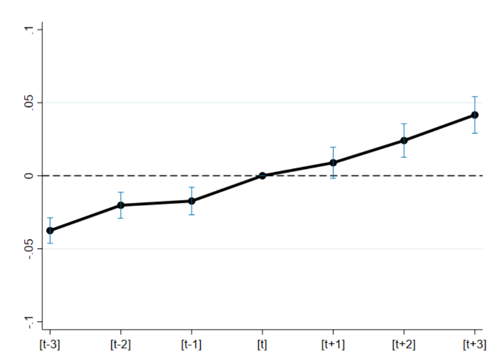


(B3) Seller citation to sold patents

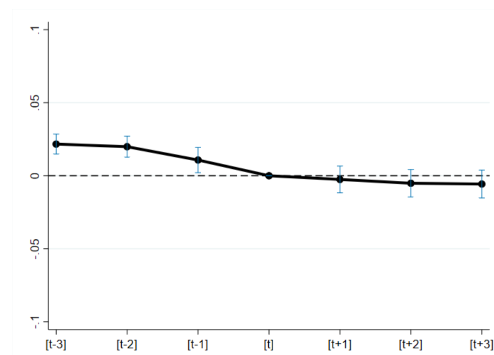
Panel C: Patent Transactions By Firms 3 Years Prior to Bankruptcy



(C1) Total citation to sold patents



(C2) Buyer citation to sold patents



(C3) Seller citation to sold patents

Table 1
Overview of Bankrupt Firms and Innovation Transactions

This table provides an overview of the sample of bankrupt firms and their innovation (patent)-selling activities during the bankruptcy reorganization process. The sample is tabulated by the Fama-French 12 industry classification (Panel A) and by year (Panel B). The sample covers all Chapter 11 bankruptcies filed by US public companies from 1981 to 2012, resolved as of mid-2016, and is manually matched with Compustat. We remove cases of financial corporations. Financial, operation, and case information is collected from Compustat/CRSP, Capital IQ, case petitions and PACER. The patent-holding information of each firm from 1976 to 2006 is accessed using the NBER patent database; we extend that database to 2012 using Bhaven Sampat's USPTO patent and citation data. Patent transactions are obtained from the USPTO patent reassignment database from 1976 to 2015.

In each panel, we report the number of bankrupt firms in each industry/year and the number of innovative firms (defined as those owning at least one patent at the time of bankruptcy filing). We report the proportion of firms that sold at least one patent during bankruptcy periods, and the ratio of patents that were sold (the ratio of sold patents is defined as zero for firms that sold no patents). Patent-selling activities are reported for the bankruptcy reorganization process—that is, between the bankruptcy filing date and the confirmation date of the reorganizing plan.

Panel A: Bankruptcy Cases and Patent Transactions by Fama-French 12 Industries

	Number of Observations		Selling [Filing, Confirmation]	
	Full Sample	Innovative Sample	% of Firms	% of Patents
Consumer Non-durables	132	49	29%	18%
Consumer Durables	77	44	52%	11%
Manufacturing	192	117	33%	10%
Oil	68	5	40%	40%
Chemicals	36	16	38%	6%
Business Equipment	231	127	46%	24%
Telecommunication	126	16	38%	31%
Utilities	24	9	44%	24%
Wholesale and Retail	305	33	24%	15%
Health care	127	48	56%	29%
Other Industries	305	54	35%	15%
Total	1,623	518	40%	18%

Panel B: Bankruptcy Cases and Patent Transactions by Filing Year

	Number of Observations		Selling [Filing, Confirmation]	
	Full Sample	Innovative Sample	% of Firms	% of Patents
1981	0	0	-	-
1982	3	1	0%	0%
1983	1	0	-	-
1984	0	0	-	-
1985	5	2	0%	0%
1986	8	4	50%	17%
1987	6	2	100%	29%
1988	14	5	20%	10%
1989	20	6	50%	21%
1990	30	10	20%	10%
1991	40	11	18%	9%
1992	41	11	18%	1%
1993	48	12	33%	5%
1994	34	8	38%	26%
1995	44	6	67%	20%
1996	43	13	31%	14%
1997	42	7	57%	36%
1998	61	18	33%	20%
1999	99	21	48%	21%
2000	118	33	52%	23%
2001	187	49	45%	22%
2002	160	57	39%	21%
2003	113	48	44%	22%
2004	62	25	32%	15%
2005	59	27	44%	15%
2006	42	17	47%	15%
2007	38	15	27%	17%
2008	67	24	25%	15%
2009	122	52	50%	16%
2010	45	11	18%	12%
2011	40	14	14%	10%
2012	31	9	67%	43%
Total	1,623	518	40%	18%

Table 2
Summary of Bankrupt Firms and Their Patents

This table reports summary statistics of bankrupt firms and their patents owned at the time of filing bankruptcy. The sample covers all Chapter 11 bankruptcies filed by US public companies from 1981 to 2012, resolved as of mid-2016, and is manually matched with Compustat. We remove cases of financial corporations. The patent-holding information of each firm from 1976 to 2006 is accessed using the NBER patent database; we extend that database to 2012 using Bhaven Sampat's USPTO patent and citation data. Patent transactions are obtained from the USPTO patent reassignment database from 1976 to 2015.

Panel A reports patent-level information. Panel B reports firm-level information collected from case petitions, Compustat/CRSP, Capital IQ, and PACER. Detailed variable definitions can be found in Section 2 of the paper and the Appendix. The variable values are measured as of the year before bankruptcy filing. For each variable, we report the mean, standard deviation, and 25th, 50th, and 75th percentiles.

Panel A: Summary Statistics of Patents Owned by Bankrupt Firms

	Patents (N=62,770)				
	Mean	Std.Dev	p25	p50	p75
Sold	0.083	0.276	0	0	0
Core ($\iota = 0.66$)	0.444	0.274	0.213	0.377	0.673
I(Core)	0.245	0.430	0	0	0
Core ($\iota = 0.33$)	0.572	0.306	0.316	0.555	0.863
Collateral	0.179	0.383	0	0	0
Scaled Citations	1.075	1.835	0.226	0.632	1.339
I(Young Patent)	0.254	0.435	0	0	1
Redeployability	0.789	0.327	0.667	1.000	1.000
MFT Liquidity	0.033	0.022	0.021	0.030	0.039

Panel B: Summary Statistics of Bankrupt Innovative Firms (Cases)

	Number of Cases (N=518)				
	Mean	Std.Dev	p25	p50	p75
Prepack(dummy)	0.197	0.398	0	0	0
Duration (in days)	510.772	537.909	203	369	641
Outcome (Acquired)	0.127	0.334	0	0	0
Outcome (Converted)	0.122	0.327	0	0	0
Outcome (Emerged)	0.512	0.500	0	1	1
Outcome (Liquidated)	0.239	0.427	0	0	0
Secured Debt Ratio	0.532	0.394	0.133	0.534	0.987
(DIP+Secured Debt)/Total Debt	0.611	0.351	0.313	0.635	0.993
HF/PE on UCC	0.377	0.486	0	0	1
Collateralization Ratio	0.317	0.504	0.032	0.205	0.454
Assets	972.825	5569.812	23.160	93.974	302.130
Leverage	0.589	0.502	0.232	0.507	0.806
ROA	-0.294	0.530	-0.412	-0.140	0.004
R&D/Assets	0.114	0.201	0.004	0.028	0.133
Patent Stock	175.145	1284.467	3	13	39

Table 3
The Determinants of Patent Sales in Bankruptcy

This table presents how innovation reallocation in bankruptcy is affected by patent-level characteristics. The analysis is conducted on a patent-level data set, and each observation is a patent p in a bankrupt firm i's patent portfolio in the year of bankruptcy filing, using the following model:

$$Sold_{ip} = \beta \cdot Core_{ip} + \lambda \times Control_{ip} + \alpha_i + \varepsilon_{ip}.$$

The dependent variable $Sold_{ip}$ is a dummy variable indicating whether patent p is sold during the bankruptcy reorganization process (from bankruptcy filing to the confirmation of the reorganization plan) by its owning firm i. *Core* is the distance between the patent and the firm's core technological expertise as defined in Section 2, with parameters $\iota = 0.66$. *Core* is also discreted into within-firm quartiles and $Core(Quartile)$ are dummy variables indicating the quartiles. The dummy indicating the lowest quartile is omitted and serves as an effective benchmark. We also use *Core (Top Patent Class of the Firm)* as a dummy indicating whether the patent is in the top patenting class of the bankrupt firm. For patent age, *I(Young Patent)* equals one if the patent was granted up to six years before the bankruptcy filing. *Scaled Citations* is the number of citations received in the first three years of a patent's life, scaled by the three-year citation of patents from its own vintage and technology class. *Redeployability* captures the extent that the patent is utilized by firms other than the owning firm, and *MFT Liquidity* captures the liquidity of the market specific to the patent's technology class. More details regarding those variables are described in the Appendix. In columns (1) to (5), the sample includes patents owned by all bankrupt public firms between 1981 and 2012; in column (6), we include patents owned by the sample of bankrupt firms that eventually emerged from bankruptcy; in column (7), we exclude cases that are prepackaged; in column (8), we include firms that appear to be in financial but not economic distress (top tercile leverage and top tercile ROA); in column (9) we focus only on patents that were applied and granted within five years prior to the bankruptcy filing. All specifications include firm fixed effects. The t-statistics based on robust standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Patent Being Sold = 1								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Core ($\iota = 0.66$)	0.022***			0.023***	0.028***	0.019***	0.029***	0.041***	0.087***
	(5.706)			(6.090)	(7.135)	(4.825)	(6.643)	(2.603)	(7.578)
Core (4th Quartile)		0.025***							
		(9.693)							
Core (3rd Quartile)		0.003							
		(1.311)							
Core (2nd Quartile)		0.003							
		(1.330)							
Core (Top Patent Class of the Firm)			0.016***						
			(7.474)						
I(Young Patent)				0.043***	0.042***	0.027***	0.055***	0.005	-0.010
				(14.510)	(14.261)	(9.036)	(15.889)	(0.641)	(-1.246)
Scaled Citation				0.004***	0.004***	0.004***	0.004***	0.003	0.003**
				(6.373)	(6.304)	(6.048)	(6.559)	(1.423)	(2.066)
Redeployability					0.027***	0.024***	0.027***	0.011	-0.004
					(9.225)	(8.553)	(8.593)	(0.857)	(-0.477)
MFT Liquidity					0.212***	0.086**	0.244***	-0.043	0.202*
					(4.856)	(2.060)	(5.295)	(-0.120)	(1.831)
Observations	62,720	62,720	62,720	62,720	62,720	53,582	54,263	1,726	13,527
R-squared	0.289	0.290	0.294	0.292	0.293	0.109	0.300	0.297	0.376
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
All Firms	Y	Y	Y	Y	Y				
Emerged Only						Y			
Exclude Prepack							Y		
Financial Distress Only								Y	
Recent Patents Only									Y

Table 4
Heterogeneous Effects Across Senior Creditor Control

This table presents how the phenomenon of selling core patents varies depending on the senior creditor control. Senior creditor control is captured using the fraction of secured debt in total debt (Panel A), the size of DIP financing scaled by total debt (Panel B), and time of bankruptcy filing (Panel C). In Panel A, secured debt ratio is defined as the fraction of secured debt in total debt of the bankrupt firm using information from Capital IQ and SEC filings. The analysis is conducted on a patent-level data set, and each observation is a patent p in a bankrupt firm i's patent portfolio in the year of bankruptcy filing. In columns (1), (2), (4), and (5), the sample is split based on *Secured Debt Ratio*, and then we run the main specification as in Table 3 separately. In columns (3) and (6), we present results in which we interact $Core$ with the dummy indicating high secured debt ratio, and the estimation is performed on the full sample. As a result, the coefficient on $Core \times$ High tests whether the pattern of selling core assets is significantly different for firms with high versus low senior creditor control.

Panel B follows the identical design but focuses on the heterogeneity across the impact of DIP financing. In columns (1), (2), (4), and (5), the sample is split based on the median value of the sum of secured debt and DIP financing scaled by total debt (the DIP financing value is set to zero for firms without DIP financing), and then we run the main specification as in Table 3 separately. In columns (3) and (6), we present results in which we interact $Core$ with the dummy indicating the DIP status. As a result, the coefficient on $Core \times$ High DIP tests whether the pattern of selling core assets is significantly different for firms with higher level of secured debt and DIP financing.

Panel C follows the identical design but focuses on the heterogeneity across time series. In columns (1), (2), (4), and (5), the sample is split based on whether the bankrupt firm filed before or after 2000, and then we run the main specification as in Table 3 separately. In columns (3) and (6), we present results in which we interact $Core$ with the dummy indicating Post-2000. As a result, the coefficient on $Core \times$ Post 2000 tests whether the pattern of selling core assets is significantly different for firms that filed bankruptcy before vs. after 2000.

The dependent variable $Sold_{ip}$ is a dummy variable indicating whether patent p is sold during the bankruptcy reorganization process (from bankruptcy filing to the confirmation of the reorganization plan) by its owning firm i. $Core$ is the distance between the patent and the firm's core technological expertise as defined in Section 2, with parameters $\iota = 0.33$. $I(Core)$ is a dummy variable indicating whether the patent is at the within-firm top quartile. All regressions include control variables *I(Young Patent)*, *Scaled Citations*, *Redeployability*, and *MFT Liquidity* as defined in the text. All specifications include firm fixed effects. The t-statistics based on robust standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Heterogeneities across secured debt ratio

	Patent Being Sold = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Secured Debt Ratio =	High	Low	Interacted	High	Low	Interacted
Core	0.047***	0.005	0.012**			
	(8.349)	(0.913)	(2.438)			
Core x High			0.025***			
			(3.849)			
I(Core)				0.065***	-0.017***	-0.017***
				(19.780)	(-6.226)	(-6.453)
I(Core) x High						0.081***
						(19.165)
Observations	23,378	33,944	57,322	23,378	33,944	57,322
R-squared	0.157	0.235	0.206	0.169	0.236	0.211
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Panel B: Heterogeneities across DIP financing

	(1)	(2)	(3)	(4)	(5)	(6)
(DIP+Secured Debt)/Total Debt =	High	Low	Interacted	High	Low	Interacted
Core	0.043***	0.009*	0.009*			
	(8.055)	(1.676)	(1.709)			
Core x High			0.034***			
			(4.406)			
I(Core)				0.063***	-0.016***	-0.016***
				(19.861)	(-5.837)	(-5.967)
I(Core) x High						0.079***
						(18.604)
Observations	23,101	32,096	55,197	23,101	32,096	55,197
R-squared	0.193	0.190	0.191	0.193	0.190	0.191
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Panel C: Heterogeneities across time-series, pre- and post-2000

	(1)	(2)	(3)	(4)	(5)	(6)
Time period	Post-2000	Pre-2000	Interacted	Post-2000	Pre-2000	Interacted
Core	0.034***	-0.014**	-0.014			
	(8.040)	(-2.052)	(-1.319)			
Core x Post 2000			0.049***			
			(4.136)			
I(Core)				0.027***	-0.003	-0.003
				(11.955)	(-0.727)	(-0.468)
I(Core) x Post 2000						0.030***
						(4.075)
Observations	57,175	5,595	62,770	57,175	5,595	62,770
R-squared	0.281	0.516	0.294	0.282	0.516	0.295
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Table 5
Creditor Rights, Patent Collateral, and Patent Sales in Bankruptcy

This table studies the determinants of patent collateral, and the reallocation of collateralized patents in and out of the bankruptcy process.

Panel A: Core Innovation and Patent Collateralization
In Panel A, we perform a cross-sectional regression to explore the determinants of whether a patent is required to be collateralized by a creditor. The sample is all USPTO-granted patents through 2013 obtained through the NBER patent data project. Patent collateral dummy *Collateral* is coded using the USPTO patent assignment database. All other variables are defined in the Appendix. We control for grant year and technology class fixed effects, and standard errors are clustered at both the technology class and grant year level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Collateral = 1			
	(1)	(2)	(3)	(4)
Core	0.078***	0.087***		
	(4.207)	(4.109)		
I(Core)			0.063***	0.070***
			(5.739)	(5.950)
Scaled Citation	0.005***	0.005***	0.004***	0.004***
	(4.350)	(4.477)	(4.212)	(4.354)
Redeployability		0.025***		0.025***
		(4.861)		(4.904)
Observations	1,335,442	1,335,442	1,335,442	1,335,442
R-squared	0.038	0.040	0.041	0.044
Grant Year FE	Y	Y	Y	Y
Technology Class FE	Y	Y	Y	Y

Panel B: Patent Collateralization and Patent Sales

Panel B explores the reallocation of collateralized patents in and out of the bankruptcy process. The sample is a patent-year level data set of all patents owned by a firm that eventually filed for Chapter 11 bankruptcy, from three years before to three years after filing. *I(Collateralized)* is a dummy variable indicating whether the patent is collateralized. *I(In Bankruptcy)* is a dummy variable indicating whether the firm that owns the patent is undergoing the bankruptcy process. All regressions include control variables *I(Young Patent)*, *Scaled Citations*, *Redeployability*, and *MFT Liquidity* as defined in the text. We control for firm and year fixed effects in column (1) and firm-by-year fixed effects in column (2). The t-statistics based on robust standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Patent Being Sold = 1	
	(1)	(2)
I(Collateralized) x I(In Bankruptcy)	0.071**	0.055**
	(1.976)	(2.309)
I(In Bankruptcy)	0.012	
	(1.402)	
I(Collateralized)	-0.011	-0.003
	(-0.838)	(-0.315)
Observations	470,254	470,254
R-squared	0.172	0.334
Controls	Y	Y
Year FE	Y	
Firm FE	Y	
Year x Firm FE		Y

Panel C: Creditor Control and the Sale of Collateralized Patents

Panel C presents how the phenomenon of selling collateralized patents varies depending on the senior creditor control. Senior creditor control is captured using the fraction of secured debt in total debt (columns (1) to (3)) and the sum of secure debt and DIP financing scaled by total debt (columns (4) to (6)), both previously defined in Table 4. The dependent variable $Sold_{ip}$ is a dummy variable indicating whether patent p is sold during the bankruptcy reorganization process (from bankruptcy filing to the confirmation of the reorganization plan) by its owning firm i. I(Collateralized) is a dummy variable indicating whether the patent is collateralized. All regressions include control variables *I(Young Patent)*, *Scaled Citations*, *Redeployability*, and *MFT Liquidity* as defined in the text. All specifications include firm fixed effects. The t-statistics based on robust standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Patent Being Sold = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Creditor Control=	High	Low	Interacted	High	Low	Interacted
I(Collateralized)	0.158***	0.066	0.066	0.160***	0.072	0.072*
	(4.365)	(1.590)	(1.593)	(4.556)	(1.654)	(1.657)
I(Collateralized) x High Creditor Control			0.092*			0.088
			(1.687)			(1.570)
Creditor Control Measure	*Secured Debt Ratio*			*(DIP+Secured Debt)/Total Debt*		
Observations	23,378	33,944	57,322	23,101	32,096	55,197
R-squared	0.293	0.248	0.265	0.234	0.225	0.229
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Table 6
The Level of Collateralization

This table presents how the phenomenon of selling core patents varies depending on the level of collateralization of secured debt. The analysis is conducted on a patent-level data set, and each observation is a patent p in a bankrupt firm i's patent portfolio in the year of bankruptcy filing. To determine the level of collateralization, we divide the value of secured debt to book assets into three tercile groups. Firms in the bottom tercile group are labeled as over-collateralized, and those in the top tercile are labeled as under-collateralized. Firms in the middle tercile are medium-collateralized. In columns (1), (2), (4), and (5), the sample is split based on medium and under/over-collateralization, and then we run the main specification as in Table 3 separately. In columns (3) and (6), we present results in which we interact *Core* with the dummy indicating the medium level of collateralization. As a result, the coefficient on *Core* $\times$ Medium-Collateralized tests whether the pattern of selling core assets is significantly different for firms with medium levels of collateralized debt versus under/over-collateralized debt.

The dependent variable $Sold_{ip}$ is a dummy variable indicating whether patent p is sold during the bankruptcy reorganization process (from bankruptcy filing to the confirmation of the reorganization plan) by its owning firm i. *Core* is the distance between the patent and the firm's core technological expertise as defined in Section 2, with parameters $\iota = 0.33$. $I(Core)$ is a dummy variable indicating whether the patent is at the within-firm top quartile. All regressions include control variables *I(Young Patent)*, *Scaled Citations*, *Redeployability*, and *MFT Liquidity* as defined in the text. All specifications include firm fixed effects. The t-statistics based on robust standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Patent Being Sold = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
	Medium-Collateralized	Under/Over-Collateralized	Interacted	Medium-Collateralized	Under/Over-Collateralized	Interacted
Core	0.035***	0.015**	0.015**			
	(7.371)	(2.261)	(2.473)			
Core x Medium-Collateralized			0.020***			
			(2.594)			
I(Core)				0.028***	0.019***	0.019***
				(10.847)	(5.488)	(6.005)
I(Core) x Medium-Collateralized						0.009**
						(2.161)
Observations	34,580	27,332	61,912	34,580	27,332	61,912
R-squared	0.089	0.397	0.292	0.091	0.398	0.293
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Table 7
Patent Trolls, Patent Litigation, and Innovation Sales in Bankruptcy

This table studies the role of patent trolls and patent litigation in patent sales in bankruptcy. In Panel A, we construct a sample of all patent transactions between 1981 and 2015, and we explore the probability that the patent is sold to a patent troll. The key explanatory variable is a dummy variable indicating whether the patent sale happens when the seller is in bankruptcy.

Panel B studies whether the patent selling pattern differs depending on the litigation risks of the different technology classes. Litigation risk is defined using the ratio of litigated patents in a technology class. The analysis is conducted on a patent-level data set, and each observation is a patent p in a bankrupt firm i's patent portfolio in the year of bankruptcy filing. In columns (1), (2), (4), and (5), the sample is split based on the *Litigation Risk*, and then we run the main specification as in Table 3 separately. In columns (3) and (6), we present results in which we interact *Core* with the dummy indicating high litigation risk, and the estimation is performed on the full sample. As a result, the coefficient on $Core \times$ High tests whether the pattern of selling core assets is significantly different for patents with higher litigation risks. *Core* is the distance between the patent and the firm's core technological expertise as defined in Section 2, with parameters $\iota = 0.33$. $I(Core)$ is a dummy variable indicating whether the patent is at the within-firm top quartile. All regressions include control variables *I(Young Patent)*, *Scaled Citations*, *Redeployability*, and *MFT Liquidity* as defined in the text. All specifications include firm fixed effects. The t-statistics based on robust standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Probability of selling innovation to NPEs

	Sold to Patent Troll = 1			
	(1)	(2)	(3)	(4)
I(In Bankruptcy)	0.005***	0.005***	0.020***	0.020***
	(3.848)	(3.699)	(8.728)	(8.867)
Observations	204,740	204,740	204,505	204,505
R-squared	0.000	0.001	0.291	0.292
Year FE		Y		Y
Firm FE			Y	Y

Panel B: Likelihood of litigation and patent sales

	Patent Being Sold = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Litigation Risk =	High	Low	Interacted	High	Low	Interacted
Core	0.049***	0.013**	0.010**			
	(8.553)	(2.466)	(2.255)			
Core x High			0.035***			
			(9.513)			
I(Core)				0.035***	0.013***	0.010***
				(11.126)	(4.742)	(3.426)
I(Core) x High						0.028***
						(7.504)
Observations	31,303	31,467	62,770	31,303	31,467	62,770
R-squared	0.297	0.309	0.294	0.298	0.309	0.295
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Table 8
Inventor Mobility and Innovation Reallocation around Bankruptcy

This table studies how inventor reallocation in a firm is affected by the reallocation of the inventor's patent and the bankruptcy status of the firm. We track inventor mobility using an inventor-firm-year-level data set, and each observation is an inventor l in a firm i for a particular year t. The sample includes inventors from all public firms between 1981 and 2010. We estimate the following specification:

$$\begin{aligned} InventorMobility_{lit} = {} & \beta_1 \cdot I(PatentBeingSold)_{lit} \times I(InBankruptcy)_{it} \\ & + \beta_2 \cdot I(PatentBeingSold)_{lit} + \beta_3 \cdot I(InBankruptcy)_{it} \\ & + \lambda \times Control_{lt} + \alpha_l + \varepsilon_{lit}. \end{aligned}$$

$InventorMobility_{lit}$ is a dummy variable indicating whether inventor l at year t moves to another firm in the next three to five years. $I(PatentBeingSold)$ equals one if the inventor has one or more patents sold to a firm at which the inventor is not currently working. $I(InBankruptcy)$ indicates whether year t is the year that firm i files for bankruptcy. In Panel A, we look at whether the inventor's patent being sold and the inventor's firm being in bankruptcy affect an inventor's reallocation decision. We control for inventor productivity by measuring new patents granted and the number of citations in the most recent three years. The t-statistics based on robust standard errors are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	I(Move within 3 Years)			I(Move within 5 Years)		
I(Patent Being Sold) × I(In Bankruptcy)			-0.035			-0.046*
			(-1.463)			(-1.807)
I(Patent Being Sold)	0.021***		0.021***	0.021***		0.021***
	(32.508)		(32.552)	(30.211)		(30.265)
I(In Bankruptcy)		0.047***	0.048***		0.050***	0.051***
		(12.717)	(12.830)		(12.424)	(12.592)
Inventor Level Controls	Y	Y	Y	Y	Y	Y
Observations	3,714,594	3,714,594	3,714,594	3,714,594	3,714,594	3,714,594
R-squared	0.019	0.019	0.019	0.018	0.017	0.018

Table 9
Creditor Recovery and Post-emergence Performance

This table presents the firm level analysis on the relation between innovation sales in bankruptcy and secured debt recovery rate and operating performance of firms emerging from bankruptcy. The key explanatory variables are whether the firm sells any innovation, and the fraction of sold core innovation in the pool of core innovation possessed by the bankrupt firm at Chapter 11 filing. The dependent variables are the recovery rate of secured lenders, post-emergence ROA (three-year average of EBITDA scaled by assets after emergence) and post-emergence profitability (three-year average EBITDA scaled by sales after emergence). Secured debt recovery is obtained from bankruptcy plans and disclosure statement for a subsample of our firms. Operating performance is obtained for the subsample of firms that emerged from bankruptcy and filed financial reports with the SEC. We control for the level of ROA and profitability prior to bankruptcy (as a way to account for firm-level fixed effects) and year fixed effects. The t-statistics based on robust standard errors are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Secured Debt Recovery		ROA		Profitability	
I(Sell Innovation)	0.136*		-0.128***		-0.467**	
	(1.699)		(-3.717)		(-2.165)	
Core Sold/Core		0.191*		-0.079**		-0.215
		(1.703)		(-2.187)		(-1.580)
Observations	133	133	90	90	90	90
R-squared	0.029	0.056	0.742	0.465	0.881	0.842
Year FE	Y	Y	Y	Y	Y	Y

Online Appendix (Not For Publication)

A1. Background: Asset Sales and Creditor Control in Chapter 11

This section provides a brief introduction to the institutional background on asset sales in Chapter 11 reorganization and how creditors can exert influence in this process.

Distressed and insolvent firms file for Chapter 11 to reorganize under bankruptcy court protection. In addition to setting up rules and guidelines to allow firms to restructure their debt claims, bankruptcy law provides firms the means to sell assets and pay creditors before court confirmation of a reorganization plan, most noticeably through §363 of the Bankruptcy Code. In our study, patent reallocations in bankruptcy are conducted through §363 sales.[15] This echos the trend of §363 becoming the main mechanism for firms to sell (innovation) assets in Chapter 11 reorganization (Baird and Rasmussen, 2002; Ayotte and Skeel, 2013; Gilson et al., 2016).

§363 has several unique features that facilitate asset sales in Chapter 11. Foremost, §363 offers a simplified procedure for asset sales. Selling assets through §363 requires a judge's approval and often secured lenders' consent, but not a formal vote of all creditors. This allows the debtor to conduct asset sales on an expedited basis.[16] This process typically takes a few weeks to complete. A detailed illustration of the process is outlined in Figure A.1. In contrast, asset sales through a reorganization plan must be voted on by each class of creditor and approved by a bankruptcy judge, and the process may take months or even years. Furthermore, §363 greatly improves the salability of assets by its provision of "free and clear of liens and encumbrances." This provision allows the asset buyer to be exempted from the prepetition lenders' security interest, improving the attractiveness of assets to buyers.

[15] Anecdotally, well-known large-scale innovation sales in bankruptcy, such as those of Eastman Kodak and Nortel, were all conducted through §363. We also confirm in Table A.1 and Figure 2 that the great majority of innovation sales during the bankruptcy reorganization process are via §363.

[16] Specifically, §363(b) allows the sale of a debtor's assets outside of a firm's ordinary course of business in bankruptcy, after notice and a hearing. §363(c) further authorizes the sale of properties of the estate, in the ordinary course of the business, without notice or hearing, under certain conditions. These provisions authorize the sale without approval of all creditors but require a "sound business purpose."

[Insert Figure A.1 Here.]

Even though §363 grants bankrupt firms opportunities to sell assets before plan confirmation, the nature of the assets sold and the selling procedure in restructuring are strongly influenced by senior secured lenders through three main mechanisms.

First, the debtor firm is required to ensure that the value of the secured creditors' claims is "adequately protected" in the bankruptcy process. Since §363 sale removes lenders' liens on collateralized assets, sales of these assets are typically subject to the consent of the secured lenders.[17] Moreover, secured lenders are protected by the cash proceeds from the sale. Therefore, the secured lenders' consent is critical to the sale of collateralized assets through §363.

Second, secured lenders may request the judge to terminate the debtor's exclusivity of filing a plan as well as request grant relief from the automatic stay, especially if they are worried about the diminution of their collateral interest. This serves as an important mechanism for secured lenders to push for the sale of collateralized assets. Secured lenders may use the relief or even Chapter 7 conversion as a threat to exert pressure on the management to sell assets. Their incentives are stronger when the sale proceeds are sufficiently large to cover their claims, even if the assets are sold for too low a price.

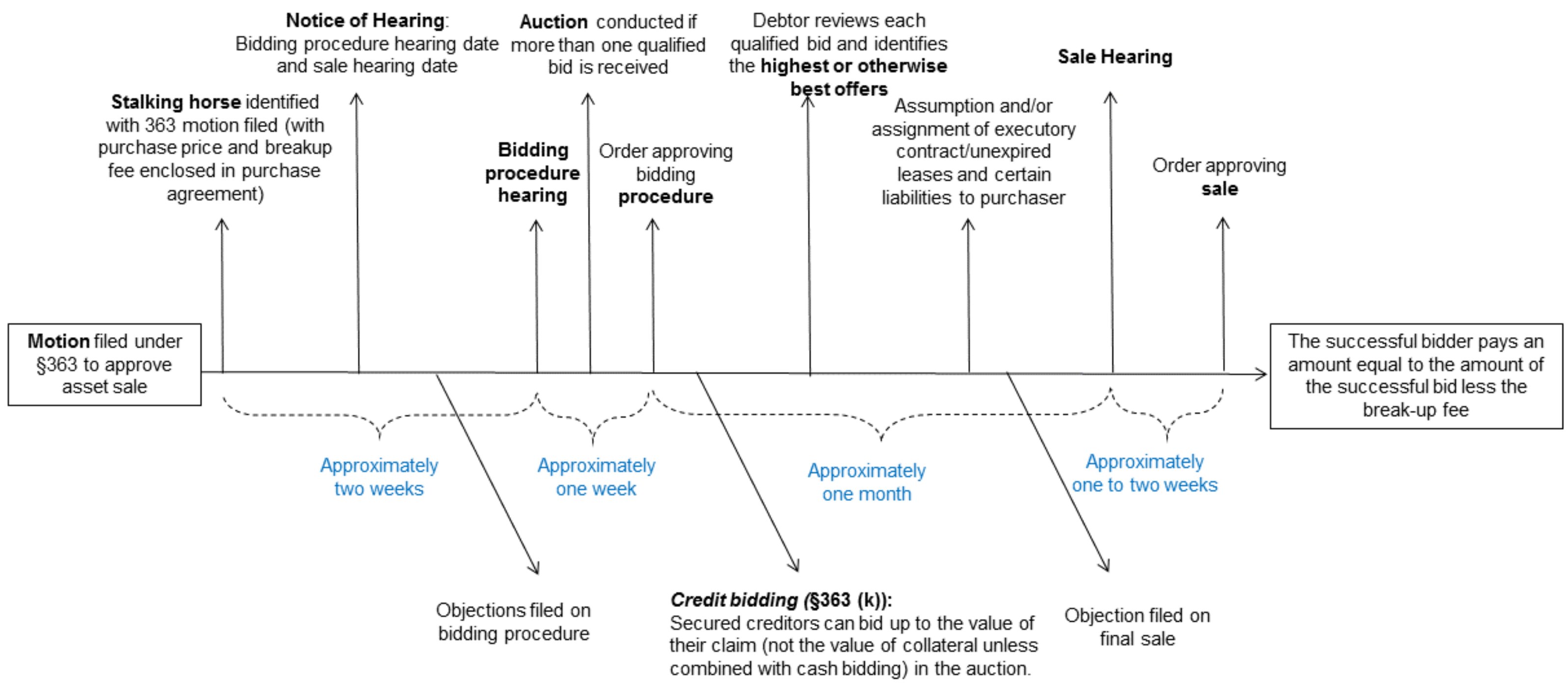
Last, prepetition lenders often re-contract with the debtor firm through debtor-in-possession (DIP) financing. These new loan contracts contain many restrictions and strict covenants as well as milestones that the debtor firm must achieve during restructuring. Specifically, the prepayment clauses that are tied to asset sale would prompt the debtor firm to pay DIP lenders upon the sale of assets. The DIP contracts, at times, afford lenders the ability to play an explicit role in asset sales through specific milestones requiring the debtor firm to set up a bidding procedure for §363 sale with the DIP lenders' approval. Moreover, creditors may re-contract with the management team to implement key employee incentive

[17] The provision to use or sell collateralized assets free and clear of liens with the consent of lenders that have security interest is explicitly laid out in §363(f), which states: "The trustee may sell property under subsection (b) or (c) of this section free and clear of any interest in such property of an entity other than the estate, only if—1. Applicable non-bankruptcy law permits sale of such property free and clear of such interest; 2. Such entity consents; 3. Such interest is a lien and the price at which such property is to be sold is greater than the aggregate value of all liens on such property; 4. Such interest is in bona fide dispute; or 5. Such entity could be compelled, in a legal or equitable proceeding, to accept a money satisfaction of such interest."

plans (Gilson and Vetsuypens, 1993; Goyal and Wang, 2017). Some of these plans request management to conduct asset sales and tie bonuses directly to proceeds from asset sales.

Figure A.1. Legal Process of Selling Innovation through §363 in Bankruptcy

This figure illustrates the legal process of selling innovation through §363 in bankruptcy. The starting point is when the §363 sale motion is filed, and the ending point is the judicial order approving the sale. The illustrated process can be generalized to sales of other assets.



A2. Identifying Patent Reallocations from USPTO Documents

This appendix provides a detailed description of the method used to identify patent transactions. We first introduce the raw data set on patent assignments and then present the methodology used to identify patent transactions; that is, patent assignments other than transfers from an inventor to the firm at which she works or from a subsidiary to its corporate parent.

A2.1. Data Sources

We begin with the raw patent assignment database, downloaded from the USPTO patent assignment files, hosted by Google Patents. A patent assignment is the transfer of (part of) an owner's property rights in a given patent or patents, and any applications for such patents. The patent transfer may occur on its own or as part of a larger asset sale or purchase. These files contain all records of assignments made to US patents from the late 1970s. The original files are then parsed and combined to serve as the starting raw data set, including all patents assigned from an inventor to the firm, from a firm to an inventor, and from one inventor (firm) to another inventor (firm).

We make use of the following information for the purpose of identifying patent transactions. First, in regard to patent assignment information, we retrieve information on the assignment date, the participating parties, including the assignee—the "buyer" in a transaction—and the assignor—the "seller" in a transaction, and comments on the reason for the assignment. Some important reasons include assignment of assignor's interest, security agreement, merger, and change of names. Second, in regard to patent information, we retrieve information on patent application and grant dates, identification numbers (patent number and application number), and patent title. We then merge the raw assignment data with the USPTO patent databases to gather additional information on the original assignee and patent technology classes. We also combine the data set with the inventor-level data maintained at HBS, which allows us to identify the inventor(s) of any given patent. Since we focus on utility patents, we remove entries for design patents.

Next, we standardize the names of the assignee and assignor in the raw patent assignment data set, original assignee names reported in the USPTO databases, and inventor names in the HBS inventor database. Specifically, we employ the name standardization algorithm developed by the NBER Patent Data Project. This algorithm standardizes common company prefixes and suffixes, strips names of punctuation and capitalization, and it also isolates a company's stem name (the main body of the company name), excluding these prefixes and suffixes. We keep only assignment records for which the assignment brief is included under "assignment of assignor's interest" or "merger"—that is, we remove cases in which the reason for the assignment is clearly not a "change of names."

A2.2. Identifying Patent Transactions

In identifying patent transactions, we use several basic principles that predict predict how patent transactions appear in the data. First, the initial assignment in a patent's history is less likely to be a patent transaction; it is more likely to be an original assignment to the inventing firm. Note that this principle is more helpful with patents granted after 1980, when the raw data set began to be systematically updated. Second, if an assignment record regards only one patent with the brief reason "assignment of assignor's interest," it is less likely to be a transaction because it is rare that two parties transact only one patent in a deal (see Serrano (2010)). Third, if the assignor of an assignment is the inventor of the patent, it is less likely that this assignment is a transaction; instead it is more likely to be an employee inventor who assigns the patent to her employer. Fourth, if both the assignor and the assignee are corporations, it is likely that this assignment is a transaction, with the exception that the patent is transferred within a large corporation (from a subsidiary to the parent, or between subsidiaries). Based on these principles, the algorithm below is a process in which we remove cases that are unlikely to be patent transactions. The steps we take are as follows:

1. Check whether the assignment record date coincides with the original grant date of the patent (the date the patent was first issued). If it does, we label the assignment as a "non-transaction," and it is removed from the data set. Otherwise, we move to Step 2.

2. Check whether the patent assignment record contains only one patent, and is the first record for this patent, with "assignment of assignor's interest" as the assignment reason.

If the answer is affirmative, we move to Step 3. Otherwise, the record is labeled as a "potential transaction," and we move to Step 4.

3. Compare the assignee in the assignment record with the assignee in the original patent assignment in the USPTO. Similarly, compare the assignor in the assignment record with the inventor names in the HBS patent database. If the assignee names match, or if the assignor is the patent inventor(s) plus the assignee is a firm, we then categorize the assignment as a "non-transaction," and it is removed from the data set. This constraint covers cases in which either the assignee or the assignor has slightly different names in different databases. Otherwise, the record is labeled as a "potential transaction," and we move to Step 4.

4. Perform the analysis described in Step 3 on the "potential transactions," with one minor change: when comparing the assignee in the assignment record with the assignee in the original patent assignment in the USPTO patent database, and when comparing the assignor in the assignment record with the inventor names in the HBS patent database, we allow for spelling errors captured by Levenshtein: edit distance less than or equal to 10% of the average length of the two strings under comparison, and we denote these name as "roughly equal to each other." Then, if the assignee names roughly match, or the assignor is roughly the patent inventor(s) plus the assignee is a firm, then assignment is categorized as a "non-transaction" and is removed from the data set. Otherwise, the record is kept as a "potential transaction," and we move to Step 5.

5. Compare the standardized names and stem names of the assignee and assignor in records in the "potential transactions." If the names match, this is consistent with an internal transfer, and the record is labeled as a "non-transaction." If the names do not match, the record is labeled as a "transaction."

A3. Supplementary Tables and Results

Table A.1
The Dynamics of Innovation Sales in Bankruptcy

This table tests whether bankrupt firms are more likely to sell patents during bankruptcy and the time-series dynamics of such transactions. We construct a firm-quarter panel of all US public firms that have at least one valid patent grant from the USPTO (that is, a firm is included in the sample after its first patent is issued). The dependent variable is the dummy variable indicating whether the firm sells any patents in that quarter (columns (1) and (2)) and the ratio (can be 0) of patents sold over the size of the firm's patent stock as of the beginning of the quarter (columns (3) and (4)). In columns (1) and (3), the key independent variable is a dummy variable, *I(InBankruptcy)*, indicating whether the firm is undergoing bankruptcy in that quarter (between the bankruptcy filing and the confirmation of the reorganization plan). Specifically, we exploit the following model:

$$Selling_{it} = \beta\ I(InBankruptcy)_{it} + \lambda \times Control_{it} + \alpha_i + \alpha_t + \varepsilon_{it}.$$

In columns (2) and (4), the analysis is extended to characterize the dynamics of selling innovation around bankruptcy. Specifically, we exploit the following model:

$$Selling_{it} = \sum_{k=-4}^{4} \beta_k\ d[t+k]_{it} + \lambda \times Control_{it} + \alpha_i + \alpha_t + \varepsilon_{it}.$$

Independent variables of interest are the set of dummies, $d[t-4], ..., d[t+4]$, indicating whether the firm-quarter observation fits into the $[-4, +4]$ time frame of the bankruptcy filing. We include both firm and year fixed effects to absorb time-invariant selling intensity at the firm level, as well as time trends in the market for innovation. The t-statistics based on standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Patent Being Sold		% of Patents Sold	
I(In Bankruptcy)	0.039***		0.022***	
	(10.828)		(23.784)	
d[t-4]		0.019**		0.002
		(2.192)		(0.842)
d[t-3]		0.011		-0.001
		(1.219)		(-0.245)
d[t-2]		0.013		0.002
		(1.465)		(0.948)
d[t-1]		0.015*		0.002
		(1.695)		(0.969)
d[t]		0.037***		0.021***
		(4.274)		(9.427)
d[t+1]		0.096***		0.055***
		(11.054)		(24.207)
d[t+2]		0.043***		0.023***
		(4.984)		(9.961)
d[t+3]		0.013		0.017***
		(1.521)		(7.621)
d[t+4]		0.020**		0.009***
		(2.273)		(4.012)
Observations	732,208	732,208	732,208	732,208
R-squared	0.246	0.246	0.021	0.021
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
F-Test				
d[t]-d[t-1]		3.349		36.12
p-value		0.067*		0.000***
d[t+1]-d[t-1]		44.28		273.10
p-value		0.000***		0.000***
d[t+2]-d[t-1]		5.484		40.97
p-value		0.019**		0.000***

Table A.2
Summary of Bankrupt Firms with No Innovation

This table reports summary statistics of bankrupt firms that do not own any patent at the time of bankruptcy filing. The sample covers all Chapter 11 bankruptcies filed by US public companies from 1981 to 2012, resolved as of mid-2016, and is manually matched with Compustat. We remove cases of financial corporations. This table reports firm-level information collected from case petitions, Compustat/CRSP, Capital IQ, and PACER. Detailed variable definitions can be found in Section 2 of the paper and in the Appendix. The variable values are measured as of the year before the bankruptcy filing. For each variable, we report the mean, standard deviation, and 25th, 50th, and 75th percentiles. The last two columns report the differences between bankrupt firms with no patent and innovative bankrupt firms and T-test on their means.

	Number of Cases=1,105					Non-innovative − Innovative	
	Mean	Std.Dev	p25	p50	p75	Difference	T-test
Prepack	0.212	0.409	0.000	0.000	0.000	0.015	(0.681)
Duration (Days)	488.992	549.284	180.000	355.000	607.500	-21.780	(-0.749)
Outcome (Acquired)	0.109	0.311	0.000	0.000	0.000	-0.019	(-1.109)
Outcome (Converted)	0.162	0.369	0.000	0.000	0.000	0.040	(2.130)*
Outcome (Emerged)	0.500	0.500	0.000	0.000	1.000	-0.012	(-0.452)
Outcome (Liquidated)	0.230	0.421	0.000	0.000	0.000	-0.010	(-0.423)
Secured Debt Ratio	0.529	0.358	0.200	0.519	0.888	-0.003	(-0.122)
(DIP+Secured Debt)/Total Debt	0.588	0.326	0.306	0.611	0.908	-0.023	(-0.985)
HF/PE on UCC	0.395	0.490	0.000	0.000	1.000	0.018	(0.360)
Collateralization	0.387	0.449	0.102	0.290	0.523	0.070	(2.235)**
Assets	591.160	4581.978	25.955	88.393	222.100	-381.665	(-1.252)
Leverage	0.629	0.461	0.306	0.566	0.834	0.044	(1.656)
ROA	-0.242	0.589	-0.285	-0.104	0.007	0.053	(1.630)
R&D/Assets	0.060	0.202	0.000	0.000	0.006	-0.055	(-3.883)***
Patent Stock	0	.	.	.	.		

Table A.3
Innovation Redeployment in Bankruptcy—Logit Regression

This table presents how innovation reallocation decisions in bankruptcy are affected by patent-level characteristics using logit regressions (marginal effects reported). The analysis is conducted on a patent-level data set, and each observation is a patent p in a bankrupt firm i's patent portfolio in the year of bankruptcy filing, using the following model:

$$Sold_{ip} = \ \beta \cdot Core_{ip} + \lambda \times Control_{ip} + \alpha_i + \varepsilon_{ip}.$$

The dependent variable $Sold_{ip}$ is a dummy variable indicating whether patent p is sold during the bankruptcy reorganization process (from bankruptcy filing to the confirmation of the reorganization plan) by its owning firm i. *Core* is the distance between the patent and the firm's core technological expertise as defined in Section 2, with parameters $\iota = 0.33$ or 0.66. For patent age, *I(Young Patent)* equals one if the patent was granted up to six years before the bankruptcy filing. *Scaled Citations* is the number of citations received in the first three years of a patent's life, scaled by this three-year citation of patents from its own vintage and technology class. *Redeployability* captures the extent that the patent is utilized by firms other than the owning firm, and *MFT Liquidity* captures the liquidity of the market specific to the patent's technology class. More details regarding those variables are described in the Appendix. In columns (1) to (4), the sample includes patents owned by all bankrupt public firms between 1981 and 2012; in column (5), we include patents owned by the sample of bankrupt firms that eventually emerged from bankruptcy; in column (6), we exclude cases that are prepackaged. All specifications include firm fixed effects. The t-statistics based on robust standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Patent Being Sold = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
Core ($\iota = 0.66$)	0.021***		0.021***	0.024***	0.022***	0.034***
	(5.961)		(6.127)	(7.144)	(4.986)	(6.584)
Core ($\iota = 0.33$)		0.023***				
		(5.785)				
I(Young Patent)			0.038***	0.036***	0.032***	0.062***
			(14.900)	(14.288)	(9.489)	(16.165)
Scaled Citation			0.003***	0.003***	0.003***	0.004***
			(6.405)	(6.368)	(5.801)	(6.686)
Redeployability				0.022***	0.026***	0.030***
				(8.525)	(7.800)	(7.906)
MFT Liquidity				0.134***	0.074*	0.218***
				(4.333)	(1.773)	(4.806)
Observations	62,770	62,770	62,770	62,770	53,603	54,305
R-squared	0.289	0.289	0.292	0.293	0.109	0.300
Firm FE	Y	Y	Y	Y	Y	Y
All Firms	Y	Y	Y	Y		
Emerged Only					Y	
Exclude Pre-packed						Y

Table A.4
The Determinants of Patent Sales—In and Out of Bankruptcy

This table presents how innovation reallocation decisions in bankruptcy are affected by patent-level characteristics using a panel setting. The analysis is conducted on a sample that consists of repeated cross-sections of patent holdings p by firms i across years t, using the following model:

$$\begin{aligned} Sold_{ipt} = {} & \beta \cdot Core_{ipt} \times I(InBankruptcy)_{it} \\ & + \beta_C \cdot Core_{ipt} + \beta_B I(InBankruptcy)_{it} \\ & + \lambda \times Control_{ipt} + \alpha_{i,t} + \varepsilon_{ipt}. \end{aligned}$$

The dependent variable $Sold_{ipt}$ is a dummy variable indicating whether patent p is sold in year t by its owning firm i. *Core* is the distance between the patent and the firm's core technological expertise as defined in Section 2, with parameters $\iota = 0.33$. $I(Core)$ is a dummy variable indicating whether the patent is at the within-firm top quartile. I(In Bankruptcy) is a dummy variable indicating whether a firm is undergoing a bankruptcy reorganization in that year. In columns (1) and (3) we control for both year and firm fixed effects; in columns (2) and (4) we control for firm-by-year fixed effects. All regressions include control variables *I(Young Patent)*, *Scaled Citations*, *Redeployability*, and *MFT Liquidity* as defined in the text. The t-statistics based on robust standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Patent Being Sold = 1			
	(1)	(2)	(3)	(4)
Core x I(In Bankruptcy)	0.024***	0.003***		
	(23.774)	(3.159)		
Core	-0.001***	-0.001***		
	(-7.503)	(-15.478)		
I(Core) x I(In Bankruptcy)			0.021***	0.006***
			(26.077)	(6.442)
I(Core)			-0.003***	-0.003***
			(-46.758)	(-47.137)
I(In Bankruptcy)	0.001**		0.008***	
	(2.573)		(27.088)	
Observations	28,545,995	28,545,995	28,545,995	28,545,995
R-squared	0.074	0.251	0.074	0.251
Controls	Y	Y	Y	Y
Firm FE	Y		Y	
Year FE	Y		Y	
Firm x Year FE		Y		Y

Table A.5
Firm-level Summary Statistics Across Creditor Control Variables

This table reports summary statistics of innovative bankrupt firms across secured debt ratio (upper panel) and DIP financing (lower panel). This table reports firm-level information collected from case petitions, Compustat/CRSP, Capital IQ, and PACER. Detailed variable definitions can be found in Section 2 of the paper and in the Appendix. The variable values are measured as of the year before the bankruptcy filing. For each variable, we report the mean. The last two columns report the differences between bankrupt firms with high vs. low creditor control variables and T-test on their means.

	Secured Debt Ratio		Low − High Creditor Control	
	High	*Low*		
	Mean	Mean	Difference	T-test
Assets	366.010	435.457	69.447	(0.645)
Sales Growth	0.077	0.070	-0.007	(-0.141)
ROA	-0.272	-0.244	0.028	(0.768)
Patent Stock	172.096	245.036	72.940	(0.495)

	(DIP+Secured Debt)/Total Debt		Low − High Creditor Control	
	High	*Low*		
	Mean	Mean	Difference	T-test
Assets	366.109	614.563	248.454	(1.146)
Sales Growth	0.063	0.123	0.060	(1.130)
ROA	-0.260	-0.218	0.042	(1.025)
Patent Stock	358.473	96.459	-262.014	(-1.368)

Table A.6
The Presence of Strong Unsecured Creditors

This table presents how the phenomenon of selling core patents varies depending on the influence by strong unsecured creditors. We use the presence of hedge fund (HF) and private equity (PE) fund investors on official unsecured creditors' committee (UCC). The presence of hedge fund and private equity fund investor is taken from Jiang et al. (2012) and Goyal and Wang (2016). The analysis is conducted on a patent-level data set, and each observation is a patent p in a bankrupt firm i's patent portfolio in the year of bankruptcy filing. In columns (1), (2), (4), and (5), the sample is split based on whether there is a hedge fund or private equity fund investor on the UCC, and then we run the main specification as in Table 3 separately. In columns (3) and (6), we present results in which we interact $Core$ with the dummy indicating the existence of a hedge fund or private equity fund investor, and the estimation is performed on the full sample. As a result, the coefficient on $Core \times$ HF on UCC tests whether the pattern of selling core assets is significantly different for firms with and without a hedge fund investor.

The dependent variable $Sold_{ip}$ is a dummy variable indicating whether patent p is sold during the bankruptcy reorganization process (from bankruptcy filing to the confirmation of the reorganization plan) by its owning firm i. $Core$ is the distance between the patent and the firm's core technological expertise as defined in Section 2, with parameters $\iota = 0.33$. $I(Core)$ is a dummy variable indicating whether the patent is at the within-firm top quartile. All regressions include control variables *I(Young Patent)*, *Scaled Citations*, *Redeployability*, and *MFT Liquidity* as defined in the text. All specifications include firm fixed effects. The t-statistics based on robust standard errors clustered at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Patent Being Sold = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
	HF on UCC	No HF on UCC	Interacted	HF on UCC	No HF on UCC	Interacted
Core	0.007	0.030***	0.030***			
	(0.707)	(7.230)	(7.361)			
Core x HF on UCC			-0.023*			
			(-1.876)			
I(Core)				0.006	0.026***	0.026***
				(1.145)	(11.622)	(11.831)
I(Core) x HF on UCC						-0.020***
						(-2.792)
Observations	5,965	56,805	62,770	5,965	56,805	62,770
R-squared	0.304	0.292	0.294	0.304	0.293	0.295
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y