Selling Innovation in Bankruptcy*

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We analyze patent reallocation in Chapter 11 bankruptcies of innovative firms. Patent sales are prevalent and occur immediately after bankruptcy filing. Firms sell their core (i.e., technologically critical) patents; and this pattern concentrates in firms whose creditors have strong control rights. Creditors demand core patents as collateral ex ante and push for sales in bankruptcy. Additional tests suggest that those patents are not reallocated for more productive uses: patents sold in bankruptcy are less cited under new ownership, more likely to be purchased by patent trolls, and more likely to be separated from their inventors than those sold outside bankruptcy.

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Financing innovation is crucial for the growth of the modern economy, but the high degree of uncertainty associated with innovation creates tremendous financing challenges for innovative firms (Hall and Lerner, 2010; Kerr and Nanda, 2015). The high probability of failure makes the bankruptcy process particularly relevant to innovative firms' financing choices (Ederer and Manso, 2011; Hochberg et al., 2018; Mann, 2018). Ideally, to incentivize innovation, the bankruptcy system ought to provide means and tools to help innovative firms resolve the adverse situation and emerge without losing their innovative advantages (Hart, 2000; Acharya and Subramanian, 2009). Yet the question remains open as to whether the bankruptcy system is up to the task.

In this paper, we investigate the Chapter 11 bankruptcy process of innovative firms. Our analysis takes a focused approach by examining the retention and reallocation of innovation assets proxied using patents. Studying innovation reallocation presents a valuable angle to examine the bankruptcy of innovative firms. First, conceptually, active asset reallocation is a defining feature of corporate bankruptcies, and economists have widely used the allocation of physical assets to examine frictions and costs in corporate bankruptcies (Maksimovic and Phillips, 1998; Pulvino, 1999; Bernstein, Colonnelli, and Iverson, 2019). Second, empirically, this approach presents us with an opportunity to assemble a novel data set using information from the United States Patent and Trademark Office (USPTO) and from Public Access to Court Electronic Records (PACER), which contain 30 years of detailed patent portfolios, systematic records of patent transactions, and the characteristics and collateralization history of the individual patents of all US public firms that filed for Chapter 11.

The point of departure of our empirical analysis is a surprising and robust finding—bankrupt firms are more likely to sell their *core*, rather than peripheral, patents during Chapter 11 reorganization. We use the measure of core patents developed and validated in Akcigit, Celik, and Greenwood (2016) and Brav, Jiang, Ma, and Tian (2018). The 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 more important for firm value. Our patent-level analysis shows that patents in the highest quartile of the core measure are 2.5 percentage points more likely to be sold than those in the lowest quartile, which is equivalent to a 30% increase from the baseline selling rate of 8.3%.

This pattern of giving up core innovation in bankruptcy is diametrically opposed to findings from the above-mentioned studies that examine patent sales in non-distressed firms. These studies use the same measure to show that non-distressed firms and firms undergoing asset restructuring under the pressure of activist equity holders sell their non-core patents—a pattern that we can replicate using non-bankrupt firms—and that divesting non-core patents creates value to the selling firm.

Why do innovative firms give up core innovation in bankruptcy? There are several explanations, which fall into two broad categories of hypotheses. On the one hand, bankrupt firms may be forced to sell due to strong control of creditors[1] whose goal is to recover debt with minimized uncertainties, even though firms want to retain valuable core innovation for post-emergence operations. On the other hand, bankrupt firms may voluntarily sell core patents because these firms, which are on average less productive, no longer possess a competitive advantage in exploiting those technologies.

The view that firms give up core innovation due to creditor control is rooted in the incompatibility between debt and innovation assets (Hall and Lerner, 2010; Kerr and Nanda, 2015). Creditors bear the downside risks of innovation while upside option value is captured by residual claimants (Stiglitz, 1985; Brown, Fazzari, and Petersen, 2009). Thus in bankruptcy creditors prefer to recover debt with certainty through selling innovation assets, rather than maximizing the value of the going concern (Acharya and Subramanian, 2009). In particular, creditors can push for asset sales because debt contracts grant them the right to repossess collateral in case of default (Shleifer and Vishny, 1997; Hart and Moore, 1998), despite the fact that these actions may result in unintended value destruction to the innovative firm ex post.

Ideally, to test 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

[1]Creditors include both senior secured creditors and unsecured creditors. This paper follows the finance literature and focuses on the control rights of senior secured creditors due to their security interest in collateralized assets and their priority status protected by the absolute priority rule of the Bankruptcy Code. We use "creditor control" to refer to senior secured creditor control unless otherwise noted.

setting, we instead undertake additional extensive data collection efforts using Capital IQ, PACER, SEC filings, and the USPTO, and perform an exhaustive set of heterogeneity tests across various measures of creditor control. We also explore the role of patent collateral and creditors' rights to seize collateral as a specific mechanism that drives our findings.[2]

We start by analyzing the patent selling pattern in bankruptcy cases with high versus low creditor control. We adopt three measures of the influence of creditors in the bankruptcy process. The first measure is the ratio of secured debt to total debt, following Carey and Gordy (2016) and Gilson et al. (2016). This measure is manually compiled using the firm's debt structure information at bankruptcy filing. We find that the pattern of selling core patents is almost purely driven by firms with an above median secured debt level. Our sample of firms with a below median value of secured debt ratio in the capital structure are not more likely (or even less likely) to sell core patents.

Our second measure captures the explicit recontracting between creditors and the bankrupt borrower through debtor-in-possession (DIP) financing immediately after Chapter 11 filing. These strict loan contracts grant senior lenders strong influence in the restructuring process (Skeel, 2004; Li and Wang, 2016). We go through the docket of each of our sample cases and download motions and orders of DIP contracts to identify whether a DIP loan is obtained and the final approved amount. We find that bankrupt firms with a higher amount of DIP financing in addition to the pre-petition secured debt are more likely to sell core patents in patent sales, while firms with lower or no DIP financing do not follow this pattern.

Third, motivated by the evidence that the Chapter 11 system has become more creditor friendly since the late 1990s (Bharath, Panchapagesan, and Werner, 2014), we divide our sample by the turn of the century to make an intertemporal comparison of the selling behavior. Our results show that

[2] A recently used exogeneous variation in studying bankruptcy is the judge random assignment and judge-level effects on Chapter 11 conversion to Chapter 7 (Bernstein et al., 2018, 2019; Iverson et al., 2018). We do not exploit this empirical design because we focus on the selling mechanism in the Chapter 11 reorganization, and our sample consists of mostly large public innovative firms whose conversion rate to Chapter 7 is low. Additionally, recent literature exploits covenant violations as an exogenous variation to creditor control (Chava and Roberts, 2008; Roberts and Sufi, 2009; Nini, Smith, and Sufi, 2012; Zhang, 2018). Since covenant violations typically trigger only technical defaults and renegotiations, rather than payment defaults and the right to seize collateral to sell, the setting does not serve the purpose of our study on bankrupt firms.

the pattern of Chapter 11 firms selling core innovation is pronounced only after 2000. Firms that filed for Chapter 11 before 2000 are, if anything, less likely to sell core innovation. Overall, these cross-sectional and time-series heterogeneity of the baseline result lend support to the hypothesis that creditors play a significant role in driving the sale of core innovation.

Admittedly, the above heterogeneity tests are not immune to the concern that creditor control is correlated with some other firm-level fundamentals, even though we show that firms in the above heterogeneous subsamples are similar on observable dimensions. To further investigate the active role of creditors, we study an important mechanism through which creditors can uniquely exert influence on patent sales—enforcing their rights against patent collateral. We present two complementary tests to shed light on how this collateral mechanism shapes the selling of core patents in bankruptcy. First, using information on the patent collateralization of all patents in the USPTO, we show that a firm's core patents are more likely to be pledged as collateral. Second, a collateralized patent is seven times more likely to be sold by a firm in bankruptcy than by a non-distressed firm. This pattern holds particularly strongly in firms with a higher level of creditor control. These pieces of evidence together suggest that enforcing rights on collateralized patents, which are typically core to the firm and of higher quality, is an important mechanism through which creditors push bankrupt firms to give up core innovation.

Unsecured creditors, unlike secured creditors, typically become the new residual claimants of the bankrupt firm after emergence and thus have strong incentives to prevent the sale of strategically important assets to preserve the long-term value of the firm. Thus, the pattern of selling core innovation under senior secured lenders' pressure should be more pronounced when there are no large unsecured creditors who can exert influence in the restructuring process. We use the presence of specialized investors, such as hedge funds and private equity firms, on official unsecured creditors' committees to capture the counter-balancing power of these creditors. Prior research shows that these investors have become a dominant force in enforcing the rights of unsecured creditors (Hotchkiss and Mooradian, 1998; Jiang, Li, and Wang, 2012). Consistent with our conjecture, the pattern of giving up core patents is weakened when such investors hold large unsecured claims.

The results thus far are consistent with the hypothesis that bankrupt firms give up their core innovation as a result of creditor control and collateral rights. But is this phenomenon indeed concerning and costly to the bankrupt firm? In the second part of the paper, we attempt to answer this question by assessing the alternative explanation: bankrupt firms may sell core patents because these firms no longer possess a competitive advantage in exploiting the technology even though they are the core assets. Under this view, selling core patents simply reflects an efficient reallocation of innovation to better users (Jovanovic and Rousseau, 2002; Hsieh and Klenow, 2009). Our tests are suggestive in nature individually, but the combined evidence will help us establish whether this alternative view is consistent with the data.

We first look into several additional aspects of those patent sales. If the patents are sold for potentially more productive uses elsewhere, we would expect to see that better firms redeploy the technologies and realize the value of the patents. However, we find evidence that is largely inconsistent with this view: (i) patents sold during bankruptcy are more likely to be purchased by patent trolls rather than by practicing users, mainly for litigation rather than exploitation purposes; (ii) there is a higher separation rate of patents and their inventors in the process of selling innovation in bankruptcy, suggesting buyers' lower intention to redeploy human capital associated with the technology; and (iii) sold patents during bankruptcy, compared to those sold during other time periods, experience a sharp decline of annual citations post-transaction, while there is a strongly increasing trend in the total number of citations before the sale, suggesting that the sold patents are of high quality but inefficiently used after the sale.

Additionally, we investigate the potential causes of bankruptcy filing and post-emergence performance. Firms go into bankruptcy due to pure financial distress or in combination with economic distress. Under the alternative efficient asset reallocation interpretation, firms that experience pure financial distress (empirically defined in our sample as high leverage with high ROA) possess competitive advantage in exploiting core technology and use the bankruptcy system to resolve temporary liquidity and capital structure issues. They are thus not expected to have a strong motive to sell core patents. Surprisingly, we find that firms suffering pure financial distress are equally likely to sell core patents. Moreover, using the sample of firms that emerge from Chapter 11, we show that when the firms sell (core) innovation in bankruptcy, secured creditors recover more at the end of the bankruptcy process. But the high recovery rate appears to come at the expense of the firms themselves—selling firms under-perform in the three years after emergence.

In summary, we provide the first study on the bankruptcy of innovative firms by focusing on the innovation reallocation process. Bankrupt innovative firms give up core technological innovation, and strong creditor control plays an important role in driving this pattern. These findings connect to the recent literature on creditor rights in innovative industries (Chava et al., 2017; Hochberg et al., 2018; Mann, 2018). A theme in this literature is that increased creditor rights and the ability to collateralize patents can enable greater debt financing for innovative firms. This paper provides supporting evidence that patent collateral protects creditors in bankruptcy. The evidence also suggests that strong creditor rights and patent collateral can be ex post costly to distressed innovative firms, highlighting the tradeoff in the process of financing innovation. The finding is consistent with the decreased use of debt in a knowledge-based economy (Titman and Wessels, 1988; Dell'Ariccia et al., 2017; Falato et al., 2018). In the same spirit of showing creditor control can be costly to innovation, Acharya and Subramanian (2009) focuses on ex ante R&D investment and show that R&D is affected by the level of creditor control in bankruptcy using a cross-country setting.

This paper also relates to studies of 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, especially trading frictions arising from industry condition or market thickness. 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 complements this literature in several ways. First, our study focuses on the reallocation of patents, arguably the most important form of intellectual property for innovative firms and for economic growth (Kogan, Papanikolaou, Seru, and Stoffman, 2017), whereas the existing research largely studies specific types of tangible assets. Second, we highlight the role of an important player in asset reallocation in bankruptcy—creditors. Third, our analysis focuses on the ex ante decision to sell or retain individual assets, in addition to investigating the ex post outcome of reallocation.

The remainder of the paper is organized as follows: Section 1 discusses sample construction and measurements, and establishes basic facts for innovation sales in bankruptcy; Section 2 presents the baseline result of selling core assets in bankruptcy; Section 3 tests the role of creditor control; Section 4 analyzes the alternative interpretations regarding efficient reallocation and offers discussions; Section 5 concludes.

1. Data and Stylized Facts

This section discusses data construction and stylized facts of innovation sales in bankruptcy. Innovative firms that file for Chapter 11 conduct asset sales in the reorganization process following rules and guidelines provided by the Bankruptcy Code. In practice, patent sales are conducted through §363 of the Bankruptcy Code, and those sales constitute our main data sample.[3] Appendix A1 provides a detailed discussion on the §363 sale process and economics therein.

First, we describe the construction of the sample of innovative bankrupt firms and relevant information (Section 1.1). Next we discuss how to identify patent transactions using USPTO data and merge those transactions with our bankrupt firm sample (Section 1.2). We then discuss key measurements (Section 1.3) and stylized facts of innovation sales in bankruptcy (Section 1.4).

1.1. The Bankruptcy Sample

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

[3] Anecdotally, well-known, large-scale innovation sales in bankruptcy, such as those of Eastman Kodak and Nortel, were conducted through §363.

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 (146 cases), were pending as of mid-2016 (5 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.[4]

The following key information is then collected for each case from Bankruptcydata.com and PACER: the date of Chapter 11 filing, the court where the case is filed, the judge overseeing the case, whether the case is prepackaged or renegotiated,[5] 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.

To measure creditor control in the bankruptcy process, we first follow Carey and Gordy (2016) and Gilson et al. (2016) to construct *Secured Debt Ratio*, which is defined as the fraction of secured debt in total debt of the bankrupt firm. We resort to Capital IQ (capital structure details section) and last 10-K or 10-Q filings through EDGAR to compile detailed information on the debt structure and debt instruments on the firm's balance sheets 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.

[4]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.

[5]A bankruptcy case is defined as 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. If the debtor negotiates the plan with fewer than all classes or obtains the acceptance of fewer than all classes necessary to confirm the plan before the bankruptcy case is filed, then the case is regarded as prenegotiated. For robustness tests, we exclude both prepackaged and prenegotiated cases from our analysis.

As an alternative measure for senior lender influence, 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.[6] For cases with incomplete dockets, we search bankruptcy plans and news in LexisNexis and Factiva to verify whether the bankruptcy court granted DIP financing and record the amount of the loan when such information is available.

Furthermore, we use whether hedge funds or private equity funds sit on the official unsecured creditors' committee (UCC), which is the committee that is composed by the seven largest unsecured creditors who are willing to represent unsecured creditors, to measure the influence of unsecured creditors in the restructuring process. We collect this information from BankruptcyData.com, PACER, and news searches in Factiva and LexisNexis, following Jiang, Li, and Wang (2012) and Goyal and Wang (2016). This information is available for a large proportion of our sample firms.

We use Compustat for financial statement data reported as of the last fiscal year before the bankruptcy filing. The key financial variables we construct include leverage (debt in current liabilities and long-term debt, scaled by book assets), ROA (the ratio of EBITDA to book assets), and R&D expenses scaled by book assets. All variables are winsorized at the 1% and 99% levels.

1.2. Patent Data: Profiles, Transactions, and Collateral

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 fundamental feature of the innovation. It also records the number of lifetime citations received by each patent as well as the sources of those

[6] 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. 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.

citations, which helps 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 (2019), 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.[7] We follow Mann (2018) and again use the USPTO patent reassignment database to identify patents that are used as collateral and the exact timing of the loan.

[Insert Figure 1 Here.]

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 for our study. Figure 1 presents the annual distribution of 518 innovative firms for our study, representing 32% of the Chapter 11 sample. 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,

[7] 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 process 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.

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%).

1.3. Key Variables

1.3.1. Core Patents. To measure whether a patent is core or peripheral to its owning firm, we follow Akcigit, Celik, and Greenwood (2016), who formalize the distance between a patent p and a firm 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, $\iota = 0.66$ is used 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, Celik, and Greenwood (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 formula (1), therefore, is calculated based on the technological 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.

The *Core* measure captures the importance of a patent in the owning firm's technology portfolio. Akcigit et al. (2016) and Brav et al. (2018) show that core patents are of greater value to the firm. They also provide evidence, which is reconfirmed below, that firms outside of bankruptcy tend to sell patents that are non-core (or equivalently, peripheral) and that selling non-core patents is value-adding. Conceptually, these empirical patterns mean that this measure captures to which degree a firm's value relies on each individual technology.

1.3.2. Patent-level Control Variables. We use patent citations to measure the general quality of a patent. Specifically, our measure $Scaled\ Citation_p$ 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. $I(YoungPatent)_{pt}$ is an indicator variable that equals one if the patent was granted within the past six years (Serrano, 2010).

$Redeployability_p$ is a patent-level measure that 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. To be consistent with the literature (Lerner, Sorensen, and Strömberg, 2011), we focus on the self-citing intensity within three years of a patent being granted, a factor that is shown to be relevant in measuring such concepts. Higher *Redeployability* means that the patent is more applicable by outside users.

We use $MFTLiquidity_{pt}$, a patent-year-level variable, to capture the annual likelihood that a patent p could be sold in year t in the market for technology. We follow Hochberg, Serrano, and Ziedonis (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.

1.4. Stylized Facts: Selling Innovation in Bankruptcy

Stylized Fact 1: *Selling innovation in bankruptcy is pervasive.*

We investigate how often firms sell innovation during bankruptcy reorganization (from the bankruptcy filing to the confirmation of the reorganization or liquidation plan). Table 1 presents bankrupt firms' intensity of selling innovation, tabulated based on their industries, defined by the 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 (defined as those that own at least one patent when filing bankruptcy), the proportion of firms that sold patents during bankruptcy reorganization, and the percentage of patents sold.[8]

[Insert Table 1 Here.]

Selling innovation during bankruptcy is a surprisingly pervasive phenomenon. Forty percent of bankrupt innovative firms sell at least one patent in the reorganization process, and patents transacted account for about 18% of their patent stock. A cross-sectional comparison in Panel A suggests that the intensity of selling innovation 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 selling innovation, 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 has remained at a fairly stable level since the early 1980s.

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

[Insert Table 2 Here.]

We also 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) to examine the selling intensity of bankrupt firms compared to other patent-holding firms and other non-bankrupt periods. The key independent variable is a dummy variable, *I(In Bankruptcy)*, indicating whether the firm is undergoing a bankruptcy reorganization in that quarter.[9] The results are shown in Table 2 columns (1) and (3). The intensity of selling innovation during bankruptcy is significantly higher than that of non-bankrupt innovative firms. The 0.039 in column (1) indicates that bankrupt firms are 3.9 percentage points more likely to sell a patent in each quarter. This is a 76% increase from the base rate of patent selling outside bankruptcy. Those firms are predicted to sell approximately 2.2% more of their patent portfolios every quarter during bankruptcy reorganizations. Overall, we find that innovation is actively traded in bankruptcy.

Stylized Fact 2: *Innovation sales concentrate within a short time window after the bankruptcy filing.*

We extend the analysis above to characterize the dynamics of selling innovation around bankruptcy. We exploit the following model in the same panel sample of firm i and quarter t:

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

where the key difference is that the independent variables of interest are now 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.

Results are reported in Table 2 columns (2) and (4). The effects are positive and significant from t to $t+4$. In column (2), the coefficient of 0.096 associated with $d[t+1]$ suggests that in the quarter immediately following the bankruptcy filing, the probability of selling a patent is 9.6%

[9] We categorize the dummy as one for cases in which the firm's bankruptcy process occurs in part of the quarter.

higher than the benchmark. Comparing coefficients of $t-1$ and $t+1$, 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 (column (4)), the increase is even more dramatic.

[Insert Figure 2 Here.]

The increase in post-filing innovation 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. Importantly, we do not observe any secular trends before bankruptcy filings in Figure 2. In sum, firms sell innovation within a short time window after bankruptcy filing. The selling pattern is consistent with Chapter 11 firms' selling assets quickly through §363 of the Bankruptcy Code, as described in Appendix A1.

Stylized Fact 3: *Innovation sales are front loaded in asset sales in bankruptcy.*

Naturally, the next question is—how does the selling behavior of innovation compare to those of other assets? If innovation assets are particularly vulnerable in bankruptcy, one would expect innovation to be sold more aggressively than other assets. This question is difficult to answer since asset holding and sales data are generally unavailable. To overcome this data challenge, we compare the dynamics of innovation sales and other asset sales through §363 using manually collected court records for a subsample of our 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 both the total number of these sales from the quarter of filing to four quarters after filing and 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, bankrupt firms sell a disproportionately large number of patents at the early stage of the asset reallocation process. In other words, patents appear to be front-loaded in asset sales.

2. Baseline Results: Selling Core Patents in Bankruptcy

2.1. Summary Statistics

Table 3 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.[10] 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 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

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

0.039 at the 75th percentile.

[Insert Table 3 Here.]

Panel B of Table 3 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% of total debt, on average. DIP financing in bankruptcy adds another 8% to make the ratio of DIP and secured debt over total debt about 61%. 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. Hedge funds and private equity funds sit on the unsecured creditors' committee (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.[11] In addition, a typical firm in our sample experiences negative ROA and carries high leverage at the time of Chapter 11 filing.[12]

2.2. Baseline Results

The baseline analysis examines the type of innovation sold 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:

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

[11] 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.

[12] In Table A.1 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.

$Sold_{ip}$ is a dummy variable indicating whether patent p is sold during bankruptcy reorganization by its owning firm i. The key explanatory variable is *Core*, for which both the continuous and categorical versions are used. We control for such patent characteristics as the scaled number of citations, patent age, *Redeployability*, *MFTLiquidity*, and firm-specific patent transaction intensities using firm-level fixed effects. In addition, firm fixed effects largely subsume time fixed effects because observations from each bankrupt firm are from the same filing year. Standard errors are clustered at the firm level.

[Insert Table 4 Here.]

Table 4 presents the regression results of equation (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%) as reported in Table 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 *Core* with parameter $\iota = 0.33$, and find similar results.

In column (4) we control for patent age and scaled citations. Consistent with the prior literature, younger and highly cited patents are more likely to be transacted. In column (5) we also control for patent redeployability and the liquidity of the market for technologies. Both of them strongly and positively affect the patent selling decisions, suggesting that bankrupt firms make asset selling decisions that intend to avoid the widely documented fire-sale costs.

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. 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 buyer before the bankruptcy filing. The results are both qualitatively and quantitatively similar to the full sample presented in column (5). In Table A.2 we show that the innovation selling pattern is both economically and statistically similar when we estimate model (3) using a Logit model.

2.3. Differences Between In and Out of Bankruptcy

The pattern of selling core innovation presented in Table 4 is particularly striking given the evidence from Akcigit, Celik, and Greenwood (2016) and Brav et al. (2018) that firms sell peripheral (non-core) patents during normal times. We temporarily deviate from our main specification (3) to highlight this point in Table 5. In this analysis, we expand our bankruptcy-only sample to patents owned by all patenting firms between 1981 and 2012. Effectively, the sample consists of repeated cross-sections of patent holdings p by firms i across years t. We use the following model:

$$\begin{aligned} Sold_{ipt} = {} & \beta \cdot Core_{ipt} \times I(InBankruptcy)_{it} + \beta_C \cdot Core_{ipt} + \beta_B I(InBankruptcy)_{it} \\ & + \lambda \times Control_{ipt} + \alpha_{i,t} + \varepsilon_{ipt}. \end{aligned} \tag{4}$$

The analysis connects the patent selling decision with *Core* and uses the interaction term *Core*×I(In Bankruptcy) to capture the deviation of the pattern during years in which a firm is in bankruptcy reorganization.

[Insert Table 5 Here.]

In Table 5 column (1), we use the continuous measure of *Core* and control for firm and year fixed effects. Not surprisingly, firms are more likely to sell patents in bankruptcy as shown by the coefficient of *I(In Bankruptcy)*. In time periods outside bankruptcy, core patents are less likely to be sold, as captured by the -0.001 coefficient of *Core*. Yet the large increase in selling core patents during bankruptcy, captured by the 0.024 coefficient, completely overturns the pattern. In column (2), when controlling for firm-by-year fixed effects, we obtain similar results qualitatively. In columns (3) and (4), we use the dummy variable $I(Core)$ and also find similar results. Overall, Table 5 links the evidence in Table 4 to the earlier findings and, more importantly, highlights the uniqueness of selling core innovation during corporate bankruptcies.

3. Creditor Control in Bankruptcy and the Loss of Core Innovation

The results so far demonstrate that bankrupt firms intensely sell their innovation, and they are more likely to sell core. There are several explanations for this selling pattern, which fall into two broad hypotheses. On the one hand, bankrupt firms may be forced to sell due to strong control of creditors whose goal is to recover debt with minimized uncertainties, even though firms want to retain these valuable core innovation. On the other hand, bankrupt firms may voluntarily sell core patents because they no longer possess a competitive advantage in using them.

This section addresses the first hypothesis on creditor control. The view that firms give up 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 creditors prefer to recover debt with certainty through selling innovation assets, rather than maximizing the value of the going concern. In practice, creditors can push for asset sales as debt contracts grant them the right to repossess collateral in case of default (Shleifer and Vishny, 1997; Hart and Moore, 1998).

To test the role of creditor control, we perform an exhaustive set of heterogeneity tests (Section 3.1), explore the role of patent collateral and creditors' right to seize patent collateral (Section 3.2), and examine the role of unsecured creditors in mitigating the force of senior lender control (Section 3.3).

3.1. Heterogeneity Across Creditor Control

We explore the role of creditor control by first conducting three sets of subsample analysis using alternative proxies. Specifically, in Table 6, we run our main specifications separately for firms with high and low 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 on $Core \times High$ (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.

[Insert Table 6 Here.]

In Panel A of Table 6, we perform the main specification on subsamples categorized by above-median versus below-median value of secured debt ratio. This sorting variable is only available for after 1995 due to availability of 10-K and 10-Q filings on EDGAR, which explains the slight drop in sample size. The pattern of selling core innovation 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 4. In contrast, in firms with low secured debt ratio, 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 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.

Second, we take into consideration the use of DIP financing in bankruptcy as a source of creditor control in addition to the pre-petition secured debt discussed above. We investigate whether bankrupt firms' innovation selling behavior differs by the influence of DIP lenders. This measure is motivated by Skeel (2004), Li and Wang (2016), and Eckbo et al. (2019), who recognize that

DIP financing has become one of the most important governance levers in Chapter 11. Creditors, typically pre-petition secured lenders, use this recontracting tool to enforce their influence and control in the restructuring process. Asset sale requests, at times, can be explicitly found in the DIP financing credit agreement. To account for this additional mechanism in total creditor control, we construct the sum of pre-petition secured debt and DIP financing (zero if no DIP financing) scaled by total debt (pre-petition total debt plus DIP amount).

Table 6 Panel B presents the results on how core relates to innovation reallocation decisions in subsamples of firms categorized by above-median versus below-median value of the sum of pre-petition secured debt and DIP financing scaled by total debt. In firms with a large amount of combined pre-petition secured debt and DIP debt, the sensitivity of selling patents to *Core* is large, twice the magnitude of the whole sample presented in the baseline.

In the third set of tests, presented in Panel C, we divide our sample by the time of Chapter 11 filing and make intertemporal comparisons on innovation selling. Prior studies show that the Chapter 11 system has become more creditor friendly and market driven since the late 1990s (Baird and Rasmussen, 2002; Skeel, 2003; Bharath, Panchapagesan, and Werner, 2014), effectively changing the view that shareholders and managers can dominate the bankruptcy process. We perform the main specification on subsamples of firms categorized by the turn of the century. We find that the pattern of Chapter 11 firms selling core innovation is pronounced only after 2000. 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 to date.

Admittedly, 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, the analyses above may be confounded by unobserved economic forces that drive creditor rights and voluntary patent selling decisions of the firm. To mitigate this concern, in Appendix Table A.3 we show that firms with high vs. low levels of secured debt are observably similar to each other. More importantly, we attempt to further establish the impact of creditor control through exploring a mechanism that is unique to creditors—patent collateral and the enforcement of rights on collateral in bankruptcy. This is the theme of the next section.

3.2. Collateralization and Patent Sales

We next examine the "collateral" mechanism through which creditor control drives the sale of core innovation in bankruptcy. Several recent studies show patents, particularly the important and valuable ones, are an important asset class for collateralized financing (Hochberg et al., 2018; Mann, 2018). If core patents are collateralized ex ante for credit, and the ex post control rights allow creditors to seize and sell collateral in bankruptcy, that would drive the pattern of core patents. This mechanism will help us pin down the active role of creditors.

We perform three sets of tests to shed light on the "collateral" mechanism. First, we confirm that a firm's core patents are more likely to be pledged as collateral in general. In Table 7 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 ever is pledged as collateral. We find, 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%). In addition, we find that patents that are of higher quality, measured using scaled patent citations, are more likely to be collateralized, and patents that are more redeployable to other users are more likely to be pledged.

[Insert Table 7 Here.]

Second, we examine whether secured lenders 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 7 Panel B presents the results. In column (1), the negative coefficient of $I(Collateralized)$ shows that collateralized patents are less likely to be sold outside bankruptcy. This is sensible—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% 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 filling.

Third, we also confirm that sales of collateralized patents concentrate in bankrupt firms with stronger creditor control. In Table 7 Panel C, we use the sample of patents owned by bankrupt firms and follow the design and measurements of Table 6. 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 lenders' incentive to recover their claims together with their lien rights prompt the bankrupt firm to sacrifice collateralized and yet strategically important patents.[13]

3.3. Influence of Unsecured Creditors

The analysis thus far focuses on secured creditor control and has put to the side the influence of unsecured creditors. Unsecured creditors, different from secured creditors, are typically the new residual claimants of firm value at emergence. As a result, they have strong incentives to prevent the sale of strategically important assets and to preserve the long-term value of the bankrupt firm.

[13] In Appendix Table A.4, 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, consistent with the findings in Ayotte and Morrison (2009) on the effect of the extent of collateralization of secured debt on asset sales.

This means, the effect of secured creditor control on patent sales should be more pronounced when there are no strong unsecured creditors who can counter-balance the power of secured lenders.

Prior literature has shown that the presence of distressed hedge funds and private equity funds, which typically enter into a bankrupt firm's capital structure by purchasing large stakes of unsecured debt for "loan-to-own", have become a dominant force in enforcing the rights of unsecured creditors (Hotchkiss and Mooradian, 1998; Jiang, Li, and Wang, 2012; Ivashina, Iverson, and Smith, 2016). In fact, these large unsecured creditors, while serving on the unsecured creditors' committee (UCC), frequently object to asset sales and the terms of DIP financing, showing their dissatisfaction with certain actions initiated by secured lenders that they deem to hurt their payoffs (Ayotte and Morrison, 2009; Eckbo et al., 2019).

[Insert Table 8 Here.]

We perform the main specification on subsamples categorized by whether hedge funds and private equity funds are members of the UCC. Table 8 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 lenders' agenda for pushing patent sales is more likely to be uninterrupted when there are no strong unsecured creditors in place.

4. Alternative Explanations and Discussions

The results in Section 3 are consistent with the hypothesis that bankrupt firms give up their core innovation as a result of creditor control and collateral rights. But is this phenomenon indeed concerning and costly to the bankrupt firm? In this section, we attempt to answer this question by assessing the alternative explanation: bankrupt firms may sell core patents because these firms no longer possess a competitive advantage in exploiting the technology even though they are the core assets. Under this view, selling core patents simply reflects an efficient reallocation of innovation to better users (Jovanovic and Rousseau, 2002; Hsieh and Klenow, 2009). The fact the creditors are facilitating the reallocation may be a sign of a well-functioning bankruptcy system for innovative firms.

We develop a series of tests to assess this alternative view. At the transaction-level, we study the buyers of the innovation assets (Section 4.1), human capital-innovation separation (Section 4.2), and the post-sale exploitation of innovation (Section 4.3). We also study the potential causes of bankruptcy (Section 4.4) that could make firms' reallocation motives differ. Clearly, these tests are suggestive in nature, as a proper identification requires the observation of counterfactual patent exploitation to characterize efficient reallocation. Nevertheless, the combined tests help us to better understand the economic interpretation that is consistent with the data.

4.1. Patent Troll Purchases and Patent Litigation

We examine the type 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; Appel, Farre-Mensa, and Simintzi, 2019). They purchase patents with the purpose of bringing lawsuits against cash-rich innovative firms, and they do so in an opportunistic manner (Cohen, Gurun, and Kominers, 2018). 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 dataset of all patent transactions between 1981 and 2015, and regress the indicator of whether it is sold to a patent troll on the dummy of whether the sale happens in bankruptcy. The results are shown in Table 9 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 NPE than are out-of-bankruptcy sales (baseline rate of patent troll purchases is 1%).

[Insert Table 9 Here.]

Since patent trolls focus on the promise of litigating using patents rather than exploiting the technologies, we would see core patents in categories with high litigation risk to be more likely to be bought. To capture a patent's litigation risks, 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 9 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 means that patents sold in bankruptcy are more likely to go to patent trolls for litigation reasons than to be used in productive exploitation.

4.2. Separation of Innovation and Human Capital

We then seek evidence from the reallocation of inventors associated with sold patents. Inventors own patent-specific human capital that is hard to replace, making inventors particularly valuable in the process of innovation exploitation (Hall and Lerner, 2010). If the reallocation is a sign of redeployment of technologies to better users, one would expect to see inventors move with the patents in such transactions and buyers' preference to maintain human capital. If the selling is simply a creditor-driven transaction, particularly when non-practicing patent trolls are buyers, the inventor mobility should be less active.

We conduct the analysis in Table 10 using an inventor-firm-year-level data set extracted from the HBS Patent Database, and each observation is an inventor l in a firm i for a particular year t. We estimate the following specification:

$$\begin{aligned} InventorMobility_{lit} = & \beta_1 \cdot I(PatentBeingSold)_{lit} \times I(InBankruptcy)_{it} \\ & + \beta_2 \cdot I(PatentBeingSold)_{lit} + \beta_3 \cdot I(InBankruptcy)_{it} \\ & + \lambda \times Control_{lt} + \alpha_l + \varepsilon_{lit}. \end{aligned} \tag{5}$$

$InventorMobility_{lit}$ is a dummy variable indicating whether inventor i at year t moves to another firm in the next three (or five) years. $I(PatentBeingSold)$ equals one if the inventor l has one or more patents sold in year t 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. We control for inventor productivity by measuring new patents granted and the number of citations in the most recent three years.

[Insert Table 10 Here.]

Table 10 shows, outside of bankruptcy, inventors of sold patents leave the firm with a much higher intensity, which reflects the buyers' intention to exploit the technologies through maintaining the original research team. This is consistent with earlier findings that inventor knowledge and team-specific capital are crucial for technology redeployment (Jaravel, Petkova, and Bell, 2018). Inventors also tend to leave a company after it files for bankruptcy—that is, there is a loss of talent and human capital (Graham et al., 2016; Baghai et al., 2017). Interestingly, coefficients associated with $I(PatentBeingSold)_{lit} \times I(InBankruptcy)_{it}$ are negative and marginally significant. This finding suggests that patent buyers during bankruptcy are less likely to maintain human capital and team knowledge, thus technology exploitation appears to be less of a concern in those transactions. This echos the findings in Section 4.1 that non-practicing patent trolls are active buyers of innovation in bankruptcy. The evidence is also consistent with bankrupt firms' attempts to maintain inventors while giving up the core technologies under creditor pressure.

4.3. Post-sale Citation Dynamics

In this section, we provide further evidence by characterizing the citation dynamics of patents sold. Figure 4 plots the coefficients β_k from the following regression at the patent (p)-year (t) level:

$$Citation_{pt} = \sum_{k=-3}^{+3} \beta_k \cdot d[t+k]_{pt} + \gamma \cdot Controls_{pt} + \alpha_p + \alpha_t + \varepsilon_{pt}. \tag{6}$$

$Citation_{pt}$ 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 differ in two dimensions. First, we separately characterize the citation dynamics of patents sold in and out of bankruptcy, which is a key distinction that has been explored in the paper. 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 received from the seller (i.e., the bankrupt firm itself for in-bankruptcy sales) .

[Insert Figure 4 Here.]

Several interesting findings emerge from Figure 4. First, the overall utilization of the patents sold during the bankruptcy process experiences an “up and down” dynamic. In contrast, for sales that happen out of bankruptcy, patent citations experience a clear increase post sales following a decline beforehand (“down and up”). The magnitude is economically meaningful—in Panel (a) 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 Panel (d) 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 Panel (c)); or it could also result from that buyers in in-bankruptcy sales are patent trolls using patents for litigation.

Second, the number of citations made by the bankrupt firm remains flat prior 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 sales (Panel (f)), which partially contributes to the pre-sale decline of total citations in Panel (b). The evidence suggests that the firms sell under-exploited patents out of bankruptcy.

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.

4.4. Financial versus Economic Distress

We provide further evidence to assess the efficient patent reallocation view based on the causes of bankruptcy. Firms file for bankruptcy as a result of financial distress and/or economic distress. Firms that primarily suffer financial distress (e.g., due to high financial leverages and shortfalls of cash flow needed to meet debt obligations) use the bankruptcy process to resolve liquidity and capital structure issues. These firms have large positive going-concern values. In contrast, firms that mainly suffer economic distress (e.g., due to poor operating performance or obsolete business models) tend to use bankruptcy to restructure their businesses (Altman and Hotchkiss, 2006). A priori, if selling core innovation is due to efficient restructuring, one would expect that the pattern concentrates in economically distressed firms, and that firms in pure financial distress should keep core innovation.

Empirically, it is challenging to distinguish firms in pure financial distress from those in economic distress (Gertner and Scharfstein, 1991). Prior empirical studies use a combination of financial leverage and operating performance to determine the categorization (Asquith, Gertner, and Scharfstein, 1994; Andrade and Kaplan, 1998). According to those studies, firms with high leverage and high operating performance are likely to suffer financial (but not economic) distress. In Table 11, we divide our sample of Chapter 11 firms into terciles using leverage ratio and ROA respectively, which creates a total of nine buckets of sample firms. We treat, as being only financially distressed, firms in the bucket that is in both the top tercile of leverage and top tercile of ROA. We treat the firms that are in the bottom ROA tercile and in the bottom or middle leverage terciles, as well as firms in the bottom leverage tercile and in the bottom or middle ROA terciles as suffering both economic and financial distress (Lemmon, Ma, and Tashjian, 2009). Under this tight definition of financial distress, 5% of our sample firms are classified as suffering purely financial distress. We also have 78% of firms suffering some level of economic distress.

[Insert Table 11 Here.]

We follow the empirical design for the subsample heterogeneity test as before, and present the regression results for the two subsamples of bankrupt firms that suffer only financial distress (columns (1) and (4)) and a combination of financial and economic distress (columns (2) and (5)). Even though we focus on only a very small subsample of firms that are driven by purely financial distress by our definition, the pattern of giving up core assets holds equally strong as in the rest of the firms. This is inconsistent with the argument that the main results of the paper simply capture the intention of economically weak firms to restructure their businesses by giving up core assets.

4.5. Discussions

4.5.1. Creditor Rights, Bankruptcy, and Financing Innovation. One may be tempted to conclude from the evidence presented in this paper that empowering creditors in bankruptcy is detrimental to innovation. However, the issue of optimal creditor rights and innovation policy is economically 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 12 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 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. Ederer and Manso (2011) survey related literature on the ex ante incentive effects.

[Insert Table 12 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 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 creditor control 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 importance consideration in

[14] To perform this analysis, ideally we need 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.

related discussions.

4.5.2. Innovation versus Tangible Assets Sales in Bankruptcy. Our study has focused on innovation sales, and has highlighted the role of creditor control in this process. One natural question that can extend the study is how to reconcile innovation sales and the reallocation of tangible assets under the same framework. A complete answer to this question is beyond the scope of this paper and is limited by the availability of data on tangible asset that allows us to observe holdings and transactions of specific assets. However, we would like to provide some remarks on this question.

First, as documented in Section 1.4 and Figure 3 using manually coded §363 court documents, innovation sales are front loaded in asset sales in bankruptcy. These active innovation sales suggest that innovation has properties that facilitate their trade in bankruptcy. For example, patents grant legal rights to use and commercialize certain technologies. A patent transaction involves the reassignment documentation and, occasionally, with human capital. This is more easily compared to the redeployment of traditional assets such as factory plants and heavy equipment, which is costly to move and redeploy, if at all possible.

Second, the creditor control mechanism applies particularly closely to innovation assets. Creditors' aversion to uncertainty leads to innovation sales, but this may not result in the selling of critical tangible assets that have low uncertainty in recovery. This means that the effect of creditor control, which might be less of a concern for tangible assets, is worth more attention in a discussion of the bankruptcy process intending to protect and incentivize innovative firms.

5. Conclusion

This paper investigates patent sales during the bankruptcy of innovative firms. Even though innovation assets are critical for firm value, they are particularly vulnerable in bankruptcy. Patent sales in bankruptcy are prevalent and occur immediately after filing. Bankrupt firms sell their core innovation (i.e., technologically critical to the business) instead of peripheral innovation. The selling of core innovation concentrates in firms strongly controlled by creditors, who demand core and high-quality patents as collateral ex ante and push for sales of those patents in bankruptcy. The results are consistent with the view that bankrupt firms give up their core innovation due to the pressure of creditor control through the collateral mechanism. We also provide suggestive evidence that those sales are not along the lines of efficient reallocation of innovation assets. These findings are closely related to the debate over the 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, and to the design of optimal intellectual property rights.

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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.

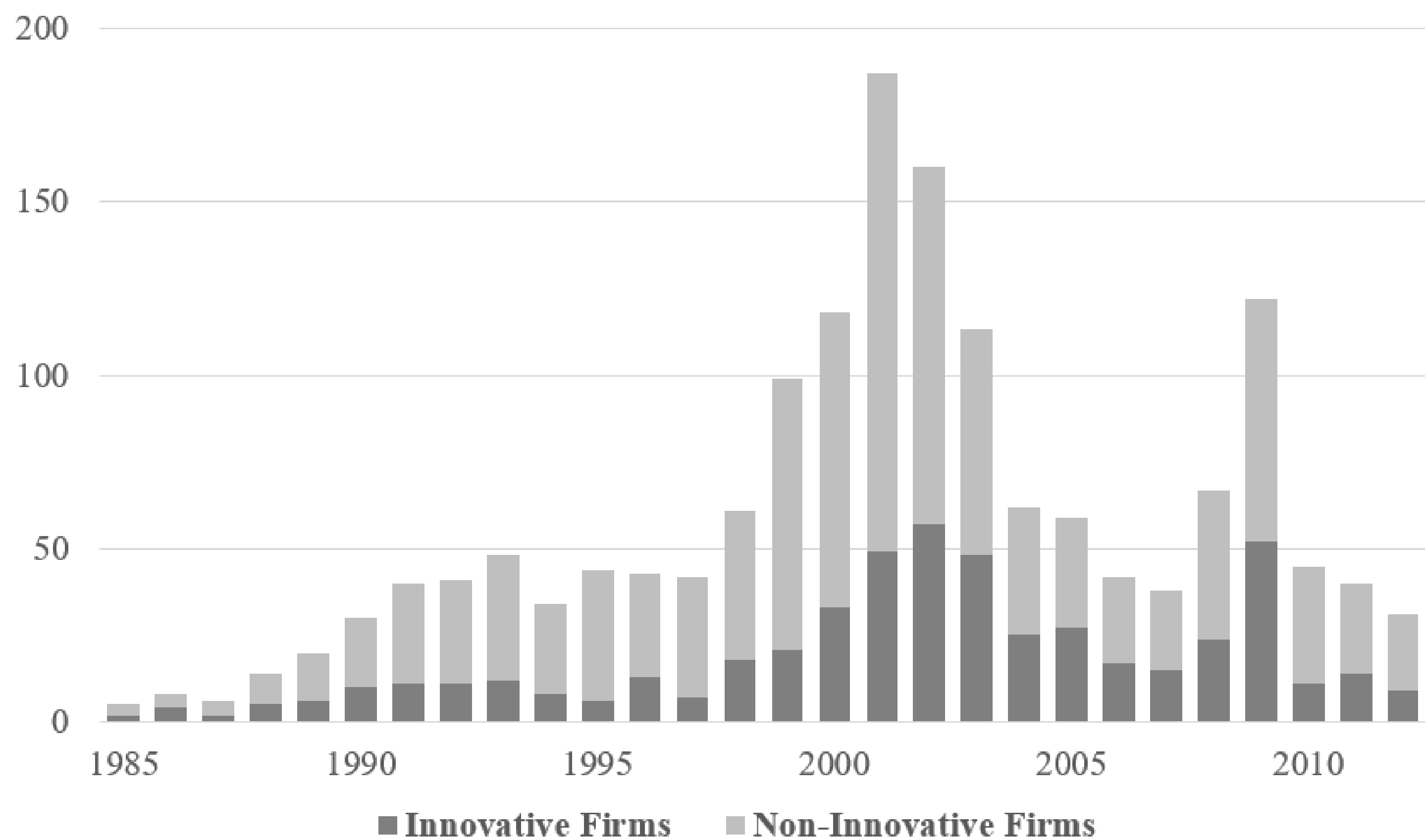
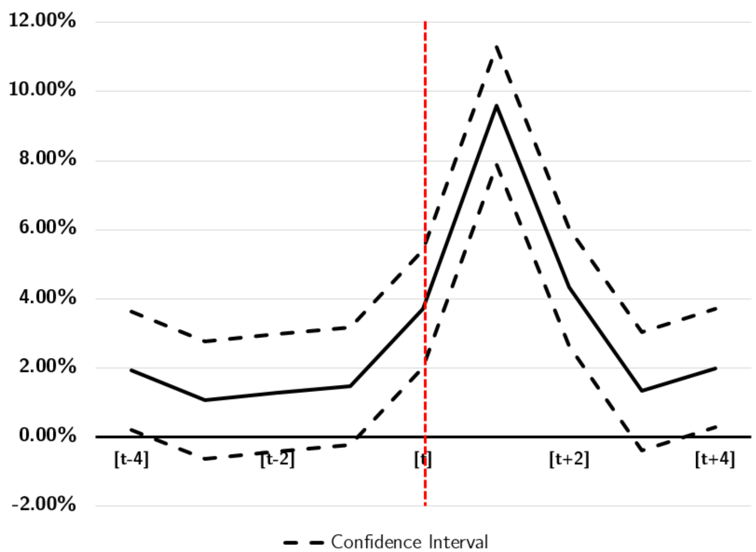


Figure 2. Selling Patents around Bankruptcy Filings

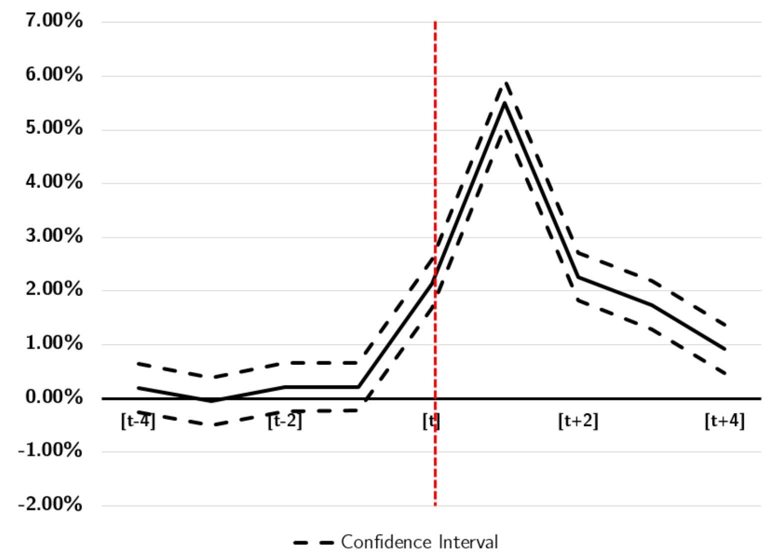
This figure presents the dynamics of the intensity of selling innovation from four quarters before the filing of bankruptcy to four quarters after the filing. We perform the analysis on a firm-quarter panel of all US public firms that have at least one valid patent grant from the USPTO (that is, a firm 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, $d[t-4], \ldots, d[t+4]$, 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.

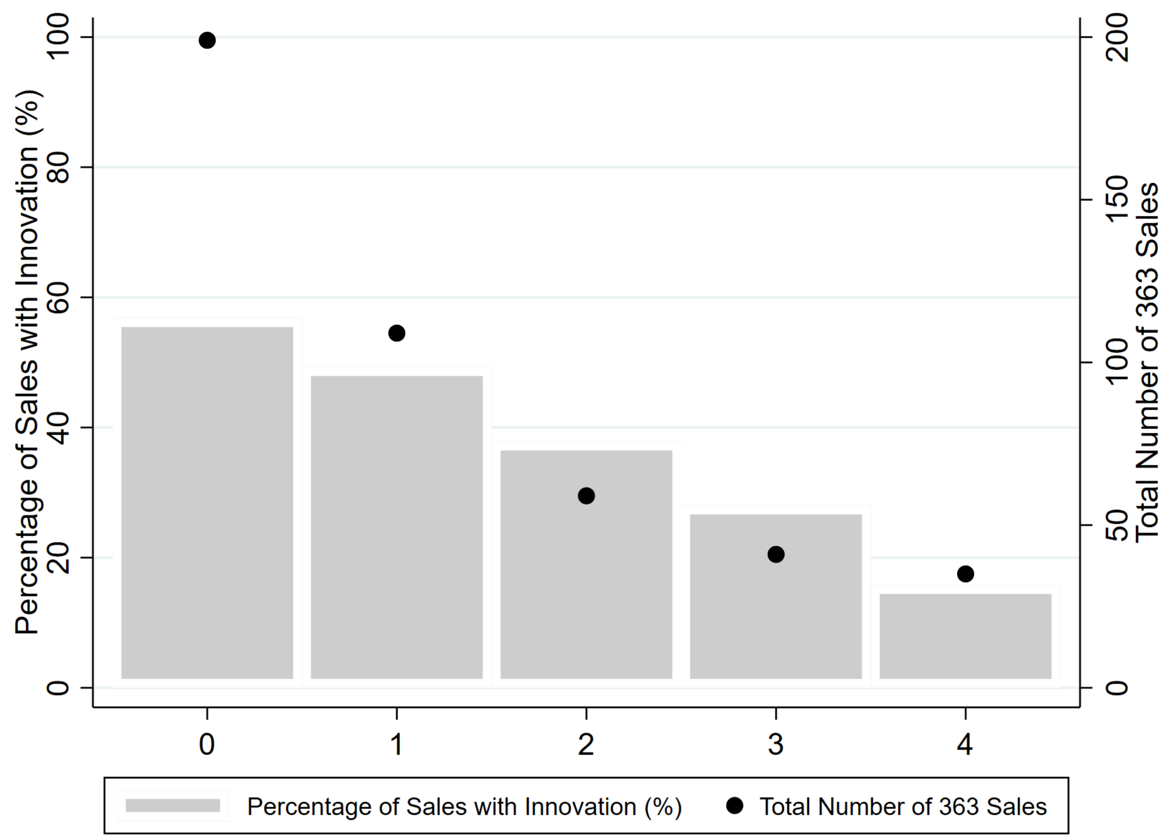
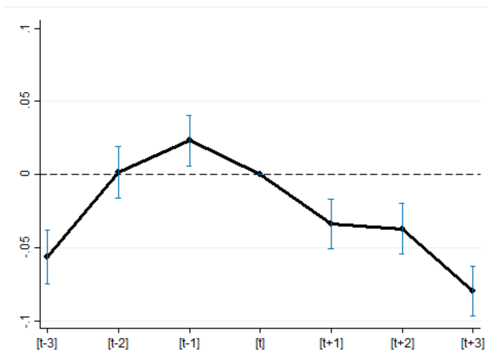


Figure 4. Citation Dynamics around Patent Transactions of Bankrupt Firms

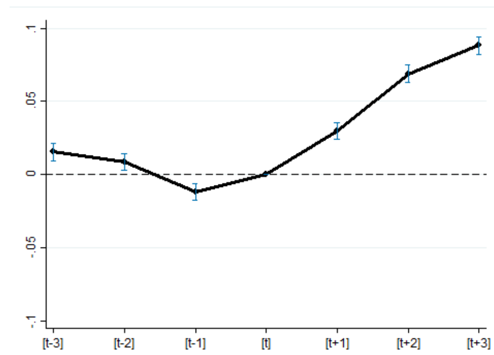
This figure plots the coefficients β_k from the following regression at the patent (p)-year (t) level:

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

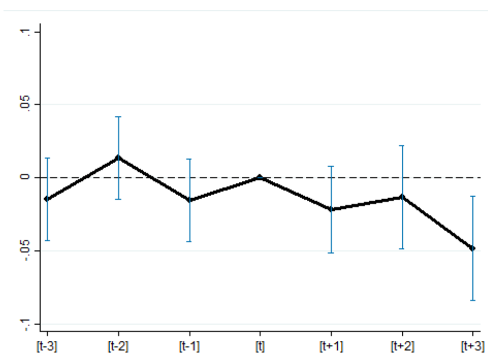
$Citation_{pt}$ is the number of new citations a patent receives in a given year, and we separately estimate using the total citations received by the patent, those received from the buyer, and those received from the seller that originally owned the patent prior to the sale. We also separately estimate 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.



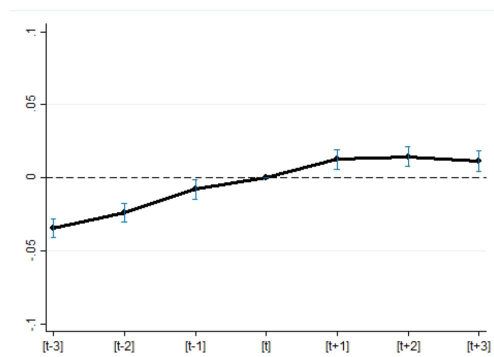
(a) Total citation, in-bankruptcy sales



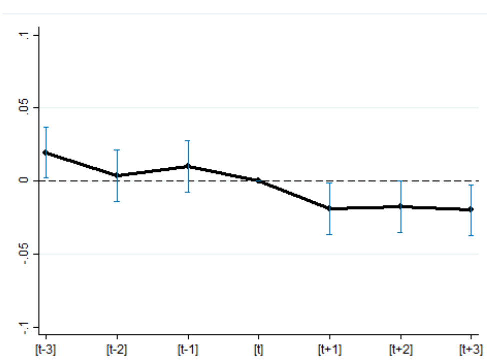
(b) Total citation, out-of-bankruptcy sales



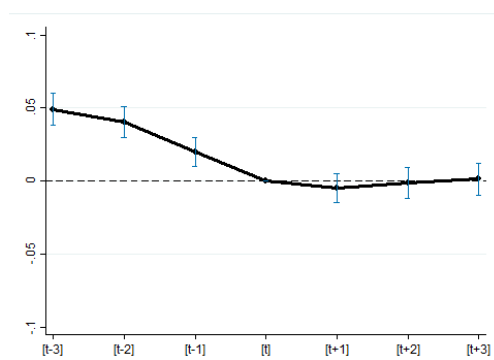
(c) Buyer citation, in-bankruptcy sales



(d) Buyer citation, out-of-bankruptcy sales



(e) Seller citation, in-bankruptcy sales



(f) Seller citation, out-of-bankruptcy sales

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 are 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
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 3
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 1 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 4
The Determinants of Patent Sales in Bankruptcy

This table presents how innovation reallocation decisions in bankruptcy are 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 1.3, with parameters $\iota = 0.33$ or 0.66. The *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. 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 (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. 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)
Core ($\iota = 0.66$)	0.022***			0.023***	0.028***	0.019***	0.029***
	(5.706)			(6.090)	(7.135)	(4.825)	(6.643)
Core (4th Quartile)		0.025***					
		(9.693)					
Core (3rd Quartile)		0.003					
		(1.311)					
Core (2nd Quartile)		0.003					
		(1.330)					
Core ($\iota = 0.33$)			0.018***				
			(5.586)				
I(Young Patent)				0.043***	0.042***	0.027***	0.055***
				(14.510)	(14.261)	(9.036)	(15.889)
Scaled Citation				0.004***	0.004***	0.004***	0.004***
				(6.373)	(6.304)	(6.048)	(6.559)
Redeployability					0.027***	0.024***	0.027***
					(9.225)	(8.553)	(8.593)
MFT Liquidity					0.212***	0.086**	0.244***
					(4.856)	(2.060)	(5.295)
Observations	62,770	62,770	62,770	62,770	62,770	53,603	54,305
R-squared	0.289	0.290	0.289	0.292	0.293	0.109	0.300
Firm FE	Y	Y	Y	Y	Y	Y	Y
All Firms	Y	Y	Y	Y	Y		
Emerged Only						Y	
Exclude Pre-packed							Y

Table 5
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 1.3, 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 6
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 book assets (Panel B), and time of bankruptcy filing (Panel C). 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 4 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 4 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 4 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 1.3, 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 7
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 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 columns (1) and firm-by-year fixed effects in columns (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 6. 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 8
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 4 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 1.3, 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

Table 9
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 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 4 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 1.3, 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 10
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 11
Heterogeneous Effects Across Financial vs. Economic Distress

This table presents how the phenomenon of selling core patents varies depending on whether the bankrupt firm suffers pure financial distress or in combination with economic distress. We treat, as being only financially distressed, firms in the bucket that is in both the top tercile of leverage and top tercile of ROA. We treat the firms that are in the bottom ROA tercile, or the bottom leverage tercile, or middle ROA and middle leverage terciles as suffering both economic and financial distress. 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 they are in financial distress or economic distress, and then run the main specification as in Table 4 separately. In columns (3) and (6), we present results in which we interact *Core* with the dummy indicating financial distress and the estimation is performed on the full sample. As a result, the coefficient on $Core \times$ Financial Distress tests whether the pattern of selling core assets is significantly different for firms in pure financial distress.

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 1.3, 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)
	Financial Distress	Economic Distress	Interacted	Financial Distress	Economic Distress	Interacted
Core	0.041***	0.023***	0.023***			
	(2.603)	(5.570)	(5.648)			
Core x Financial Distress			0.013			
			(0.627)			
I(Core)				0.034***	0.036***	0.036***
				(4.468)	(15.154)	(15.313)
I(Core) x Financial Distress						-0.006
						(-0.544)
Observations	1,726	38,167	39,895	1,726	38,167	39,895
R-squared	0.297	0.291	0.291	0.302	0.294	0.295
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Table 12
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 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

Appendix (Not For Publication)

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).
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.

Economic Distress	An indicator variable that takes a value of one if the bankrupt firm experiences economic distress, which is defined as firms in the bottom ROA tercile and the bottom or middle leverage terciles, and firms in the bottom leverage tercile and bottom or middle ROA terciles.
c. Firm Characteristics	
Assets	Total book assets in millions, adjusted to 2007 US dollars.
Size	The natural logarithm of 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.

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.

[Insert Figure A.1 Here.]

[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 2 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."

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.

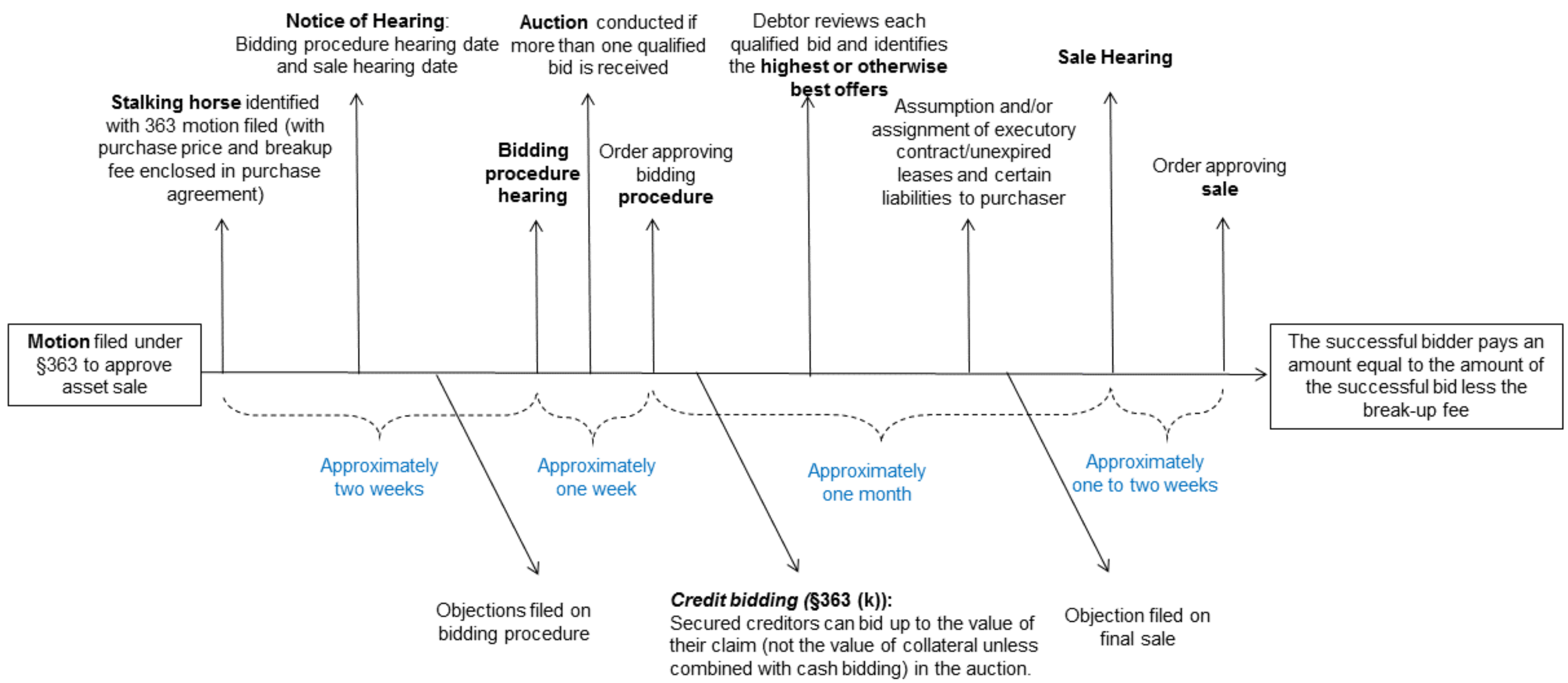
Second, secured lenders may request the judge to grant relief from the automatic stay, especially if they are worried about the diminution of their collateral interest. This serves as an important mechanism for secured lenders to push for the sale of collateralized assets. Secured lenders may use the relief 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.

[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."

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
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 1 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.2
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 1.3, 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.3
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 1 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.4
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 collaterlaization, we divide the value of secured debt to book assets into three tercel groups. Firms in the bottom tercel group are labeled as over-collateralized and those in the top tercel are labeled as under-collateralized. Firms in the middle tercel are medium-collateralized. In columns (1), (2), (4), and (5), the sample is split based on medium and under/over-collateralization, and then run the main specification as in Table 4 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 level 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 1.3, 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) Medium-Collateralized	(2) Under/Over-Collateralized	(3) Interacted	(4) Medium-Collateralized	(5) Under/Over-Collateralized	(6) 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