

# The determinants of recovery rates in the US corporate bond market<sup>☆</sup>

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## Abstract

We examine recovery rates of defaulted bonds in the US corporate bond market, based on a complete set of traded prices and volumes. A study of the trading microstructure around various types of default events is provided. We document temporary price pressure with high trading volumes on the default day and the following 30 days, and low trading activity thereafter. Based on this analysis, we determine market-based recovery rates and quantify various liquidity measures. We study the relation between the recovery rates and these measures, considering additionally a comprehensive set of bond characteristics, firm fundamentals, and macroeconomic variables.

*Keywords:* credit risk, recovery rate, corporate bonds, liquidity

*JEL:* G12, G33

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## 1. Introduction

The global financial crisis has highlighted the importance of credit risk in the pricing of financial contracts and emphasized the multifaceted nature of its key determinants: the probability of default and the recovery rate in the event of default. Traditionally, credit risk modeling has been focused on the probability of default, while the recovery rate has been set to parametric values that do not necessarily recognize its potential cross-sectional and time-series variation. However, the magnitude and variability of defaults during the crisis have emphasized the importance of obtaining more precise estimates of recovery rates, and explaining their variation across issues

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and issuers. It is now intuitively understood that recovery rates are potentially driven by many different factors: endogenous variables (such as specific characteristics of the assets involved and of the firm and industry), or exogenous factors (such as overall macroeconomic conditions or market liquidity). It is important, therefore, to document the determinants of this risk factor and to analyze their interaction effects with other dimensions of default risk. This paper aims at investigating these relationships at the issue and obligor levels for the US corporate bond market.

Most credit risk instruments, such as bonds and credit default swaps (CDS), trade over-the-counter (OTC). This makes research in this area challenging, as traded prices and volumes for these instruments cannot be observed directly from a central database. Therefore, most studies have to rely, of necessity, on quotation or trade data from a particular dealer, leaving open the question of whether the data are representative of the market as a whole. This is even more of a problem for defaulted financial instruments, as their trading can often be infrequent, resulting in stale prices, with some of the quotations or trades of individual dealers even being “off market.” In contrast, the market for US corporate bonds is an ideal laboratory for this study, since detailed data on prices and volumes are available from 2002 onwards in the Trade Reporting and Compliance Engine (TRACE) database, maintained by the Financial Regulatory Authority (FINRA). This allows us to analyze, for the first time, the prices and volumes of defaulted bonds based on a complete set of transaction data, covering all trades following default events, for the period from 2002 to 2010. As a consequence, this microstructure analysis not only permits a reliable estimate of a market-based recovery rate, but also provides an opportunity to study trading activity, and hence liquidity, at different stages following default. We combine the TRACE data set with the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database, which allows us to consider a broad set of default events, capturing formal bankruptcy filings, distressed exchanges, and downgrades to default status by rating agencies, representing payment defaults and unlikely-to-pay events.

We make three contributions in this paper. First, we provide a detailed analysis of the microstructure of trading in defaulted bonds, working with a *complete* set of default events over the most recent decade, offering crucial and interesting new insights. The study of market prices and trading behavior around different default events is important as many institutional investors are directly exposed to these post-default prices, e.g., because they have to immediately liquidate their positions, deliver the bonds through the settlement of credit default swaps (CDS) positions, or mark down the values of the defaulted bonds on their balance sheets. Furthermore, the examination of market prices provides us the opportunity to analyze *all* default events (including, e.g., distressed exchanges), and not only the outcomes of formal bankruptcy procedures, often known only years after the actual filing dates. Overall, this analysis allows us to discuss trading activity at different stages following default and to derive market-based estimates of recovery rates, which

are of fundamental relevance to various market participants.<sup>1</sup> Second, we quantify the liquidity of defaulted bonds, applying different measures in our analysis, and explore the implications for recovery risk, which turn out to be of particular importance, since defaulted bonds are potentially illiquid. Consequently, we study to what extent changes in the underlying liquidity, following default, account for the observed post-default price evolution, as default might induce pressure on prices. Third, we analyze the resulting bond recovery rates, employing a broad set of explanatory variables in our regressions to capture various aspects of recovery risk originating from bond characteristics, including bond covenants, firm fundamentals, and macroeconomic conditions, in contrast to much of the previous literature in which the analysis has typically been more narrowly focused.

Our analysis of recovery rates yields several distinct sets of findings. We examine the trading activity of the defaulted bonds, as defined by traded prices and volumes, in a time window starting 90 days before and ending 90 days after the observed default event date. We find that, although the price level is already rather low before the default event, the traded price falls significantly to its lowest level on the default day itself, to around 35% of face value, on average. The price recovers, in the first 30 days following default, to about 42% of face value and shows a less volatile evolution thereafter.<sup>2</sup> Furthermore, we find that the trading volume of a defaulted bond is relatively high on the default event day, providing evidence of temporary sell-side pressure as prices are low. This high level of trading activity dies down, within the first 30 days after default, to pre-default levels. Thus, this time window apparently represents the relevant trading period following default in which investors split up and sell larger positions in defaulted bonds. Based on these findings, we define the recovery rate of a defaulted bond as the average daily traded price per unit of face value, over the default day and the following 30 days, covering the phase of high trading activity, as we conjecture that price evolution in this time window is mostly driven by the default event itself.

We analyze these recovery rates across bonds along various dimensions. First, we analyze them across different default event types, revealing that distressed exchanges have the highest recovery rates, whereas bankruptcy filings show significantly lower recoveries. This finding provides further evidence that bondholders are confronted with lower recoveries in formal legal procedures compared to in out-of-court restructurings. Second, we find significant differences in recoveries between the default grades of the major rating agencies, which represent payment defaults and unlikely-to-pay events, respectively; in particular, the rating frameworks of Moody's and Fitch

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<sup>1</sup>These estimates should be contrasted with the *ultimate* recovery rates, which are based on the amounts paid by the firm to its bondholders at the resolution of formal bankruptcy filings.

<sup>2</sup>Note that a 40% recovery rate, which was the point estimate provided by Altman and Kishore (1996) in an early paper in this area, has been widely used in calibrations in academia and industry.

seem to incorporate recovery rate information to a greater extent than that of Standard and Poor's.<sup>3</sup> Third, we find that, among *nonfinancial* industries, utility and energy-related firms recover the most in default, while retailers recover the least. Interestingly, among *financial* firms, the banking and credit & financing industries recover the most in default, whereas the financial services industry recovers the least. Fourth, in terms of seniority levels, we find, as expected, that secured bonds recover more than unsecured and subordinated bonds. Fifth, we document a substantial variation in recovery rates over time, e.g., quarterly moving averages between 20% and 80% of face value, for the time period from 2002 to 2010.

In the main part of our analysis, we employ regression models to explain the variation in recovery rates, using a comprehensive set of bond characteristics, balance sheet ratios, macroeconomic variables, and liquidity measures (in addition to dummy variables, based on the default event type, industry, and seniority). Overall, our regression analysis explains 66% of the total variation in recovery rates, with all four groups of variables contributing to the explanatory power. We demonstrate a clear link between the defined bond-specific liquidity measures and their recovery rates. In particular, when measuring the transaction costs of trading using the price dispersion measure, we document that illiquid bonds with high transaction costs recover less following default.

Analyzing bond characteristics, we find that bonds that can be delivered into a CDS contract have a significantly higher recovery rate, possibly because of increased demand from protection buyers, who are required to physically deliver the underlying bond. In addition, we find that bond covenants significantly affect the level of the recovery rate. In particular, investment and financing covenants that provide protection for existing bondholders against potential adverse firm actions are important determinants. That is, restrictions on the investment and financing policy are an effective tool that creditors can use to increase their recovery rates.

As for the other firm characteristics, among balance sheet ratios, we find significant effects for those ratios that are motivated by structural credit risk models, i.e., the higher is the equity ratio, and the lower the default barrier, the higher will be the recovery rate. Analyzing macroeconomic variables reveals a particularly strong effect for the market-wide and industry-specific default rates. Thus, a high default rate in the market as a whole, a systematic risk factor, or a high industry-specific default rate, as an indicator of industry distress, are all linked to significantly lower recovery rates for individual bonds, following default. Along the same lines, we find a positive relation between short-term interest rates, an indicator of the business cycle, and recovery rates.

In an additional analysis, we explore the cross-sectional price properties of later post-default

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<sup>3</sup>Note that the rating frameworks of Moody's and Fitch focus on the expected loss, (see Moody's Investors Service, 2002; FitchRatings, 2013), which involves both the probability of default and the recovery rate given default. In contrast, Standard and Poor's ostensibly considers only the probability of default in its ratings (see Standard & Poor's, 2011).

periods to test whether our results depend on the particular time window chosen for the recovery rate estimation: We show that all determinants consistently explain prices within the first 90 days after default. Moreover, we find that trading activity (volume and number of trades) are important additional measures of liquidity, and explain cross-sectional differences in prices, once the sell-side pressure subsides and trading activity drops back to pre-default levels. Hence, in order to further elaborate on the importance of liquidity in default, we present evidence showing that changes in trading activity and transaction cost measures of liquidity can indeed explain observed price changes, across different post-default periods.

Overall, we provide a comprehensive analysis, going beyond the results that have been presented in the prior literature. We study the microstructure of trading activity and offer detailed insights into the stochastic nature and drivers of recovery rates by analyzing a broad set of explanatory variables rather than only providing evidence on the effects of any one factor. Our results on the effects of liquidity are particularly noteworthy, since our paper is the first, to our knowledge, to report findings on the effects of liquidity on recovery rates. The paper is organized as follows: Section 2 reviews the literature. Section 3 provides details of the data used in our analysis. Section 4 states the main hypotheses tested and the research questions addressed. Section 5 presents the methodology and explains the setup of the subsequent analysis. Section 6 provides the descriptive analysis and the results of the regression models. Section 7 concludes.

## **2. Literature review**

The literature on recovery rates can be divided into two categories: theoretical papers dealing with credit risk models, which make implicit or explicit assumptions about recoveries in default, and empirical papers analyzing past default events. Traditionally, credit risk models have been divided into structural and reduced-form models see, e.g., Altman et al. (2002) for a detailed discussion. In the basic structural models, starting with Black and Scholes (1973) and Merton (1974), the default risk of a firm is driven by the process generating the value of its assets; hence, the risk of the firm's default is explicitly linked to the volatility of its asset value. Default occurs when the value of a firm's assets is lower than that of its liabilities at maturity. In this case, the debtholders receive the residual market value of the firm's assets. Hence, in this setup, the recovery rate, as the residual value of the defaulted company's assets, is an endogenous variable that is inversely related to the probability of default. This relation becomes even more evident when structural models are used as the basis for credit portfolio analysis (see, e.g., Frye, 2000; Gordy, 2003), where asset values are modeled by market-wide factors and idiosyncratic factors, with market factors leading to a negative relation between aggregate default and recovery rates.

Several authors provide extensions to the basic Merton (1974) model.<sup>4</sup> They generally assume that default may occur at any time between the issuance and maturity of the debt, that default is triggered when the value of the firm's assets reaches a lower threshold barrier, or that bankruptcy costs arise exogenously. Interestingly, in most of these models, the recovery rate is assumed to be exogenous or independent of the firm's asset value. It is generally defined as a fixed proportion of the outstanding debt value, in terms of either face or market value, and is, therefore, independent of the probability of default.

Reduced-form models of credit risk do not condition default on the structural features of the firm (see, e.g., Jarrow and Turnbull, 1995; Duffie and Singleton, 1997; Lando, 1998). Rather, these models allow separate, explicit assumptions to be made regarding the dynamics of *both* the probability of default *and* the recovery rate. Although, in principle, a complex dependence structure can be used in such models, the recovery rate is usually assumed to be exogenous, either deterministic or stochastic, and often independent of the default probability.

It has been well documented that neither reduced-form models (see, e.g., Longstaff et al., 2005) nor structural models (see, e.g., Huang and Huang, 2012) can fully explain observed yield spreads satisfactorily. It is relevant, therefore, to try to understand the stochastic nature of recovery rates and provide evidence from past defaults, to improve the modeling of default. During the last two decades, direct attempts have been undertaken to empirically investigate the behavior of recovery rates. An important first analysis is provided by Altman and Kishore (1996), who use a data set of over 700 defaulted bond issues from 1978 to 1995, focusing on the recovery experience on the default day based on quoted prices. They analyze the effect of industry affiliation on recovery rates, and conclude that the highest average recoveries come from public utilities (70%) and chemical, petroleum, and related products (63%), and that the original rating of a bond has virtually no effect on recovery, once seniority is accounted for. Hanson and Schuermann (2004) provide similar evidence for the impact of seniority and industry affiliation, based on an analysis of a sample of around 2,000 defaults of bonds and loans. Furthermore, they study the empirical distribution of recovery rates and provide evidence that recoveries are lower in recessions. Along the same lines, Altman et al. (2005) analyze the relationship at a macroeconomic level, and conclude that the average annual recovery rates and default rates are indeed negatively correlated. They show that realized default rates in a particular year are important drivers of recoveries, whereas other macroeconomic variables, such as the gross domestic product (GDP) or the GDP growth rate, i.e., the performance of the economy, are less predictive than most theoretical papers would suggest.

Acharya et al. (2007) provide a detailed analysis of industry-wide distress and its relation to

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<sup>4</sup>Black and Cox (1976), Leland (1994), Longstaff and Schwartz (1995), Leland and Toft (1996), Anderson and Sundaresan (1996), Mella-Barral and Perraudin (1997), Collin-Dufresne et al. (2001), Goldstein et al. (2001), and Acharya et al. (2006) are examples of such analyses.

recovery rates at default. They argue that, when an industry is in distress, defaulting firms in the industry experience lower recoveries. One mechanism causing this effect is the lower ability of the distressed firm to sell assets to competitors in the same industry, as discussed in Shleifer and Vishny (1992). Using a data set from 1982 to 1999, with about 800 observations, they provide evidence that defaulted debt in industries in distress recovers 10% to 15% less on average. They also document a negative effect of aggregate default rates on the recovery rates of individual issues and provide some evidence that balance sheet ratios are of importance.

Analyzing the default event type, Bris et al. (2006) and Davydenko and Franks (2008) provide evidence that differences in creditors' rights and reorganization practices are reflected in the level of recovery rates at the time of default resolution. They compare defaults across different bankruptcy procedures, e.g., Chapter 7 versus Chapter 11 filings, as well as across different countries or jurisdictions. Altman and Karlin (2009) provide further evidence of the importance of the default event in discussing distressed exchanges. They find that, in distressed exchanges, recoveries at default are higher than in the case of other default events. Altman and Kalotay (2014) provide further evidence of industry-driven effects, focusing on the modeling of the distribution of recovery rates for defaulted loans and bonds.<sup>5</sup> Interestingly, their results are based on ultimate recoveries, i.e., the recovery at the resolution of the default, rather than the traded prices immediately following default.

Our paper extends the existing literature in new and important directions and provides detailed empirical evidence on the driving factors of recovery rates, covering a complete set of default events. Reviewing this literature, the analysis provided by Acharya et al. (2007) is the closest to ours. However, there are crucial differences between that paper and ours, which generally apply to the comparison of our paper with all other prior studies as well. First, Acharya et al. (2007) employ a rough proxy for the recovery rate since they use the prices of the securities at the time of *emergence from default* (which can be several years after the actual bankruptcy filing) and discount them to the time of default using a high-yield bond index. As a consequence, they cannot rely on detailed and accurate market microstructure data *at the time of default* as presented in this paper, which could influence their results. This shortcoming is basically common to all other prior studies, which have to rely on (rough) proxies for the recovery rates as well, and mostly employ price/quotation information at one point in time without being able to assess possible alternatives directly related to the market information at the time of default. Second, our setup allows us to directly address the liquidity of defaulted securities, for the first time. Third, we make use of a far more comprehensive list of instrument- and firm-specific variables and analyze a broader set

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<sup>5</sup>See Altman et al. (2010) for a further discussion of the differences between the recovery rates of loans and bonds.

of default events. Therefore, we can provide a particularly detailed analysis of the determinants of recovery rates going beyond the scope of the presented literature.

### 3. Data

This paper relies on several data sources that we combine to analyze recovery rates in the US corporate bond market. First, we identify the default events by type, using the Mergent Fixed Income Securities Database and NYU Salomon Center Master Default Database. These databases provide detailed information on all Chapter 11 filings, distressed exchanges, and downgrades to a default rating grade.<sup>6</sup> These events cover virtually the whole spectrum of default scenarios, i.e., formal bankruptcy filings to informal unlikely-to-pay events. Overall, we observe 1,270 default events for 534 firms for the time period from July 2002 to October 2010.<sup>7</sup> Table 1 presents the list of event types and their definitions. The first type of default event consists of Chapter 11 filings, representing formal bankruptcy procedures handled by federal courts; i.e., when a firm is unable to service its debt or repay its creditors, then it or its creditors can file with a federal bankruptcy court for protection under Chapter 11. A trustee can act as *debtor in possession*, and thus operate the business. Chapter 11 filings can be used to restructure the debt or liquidate the assets. The second type of default event comprises distressed exchanges, in which the debtor attempts to avoid formal bankruptcy by proposing a fundamental change in the existing contractual commitments to its creditors. Thus, the creditors can voluntarily agree to avoid the potential costs that might arise in a formal restructuring. Distressed exchanges have become popular in recent years, particularly since the financial crisis. The third type consists of payment defaults and unlikely-to-pay events, represented by ratings downgrades. We retrieve ratings from Moody's, Standard and Poor's, and Fitch. Ratings rank the obligor according to creditworthiness (AAA, AA, . . . , C, D), with the rating agencies providing differentiated default classes. The worst rating grade (e.g., D) indicates an actual default (payment default on a financial commitment). The second worst rating grade (e.g., C) is meant for highly speculative obligations that are considered unlikely-to-pay. Under many regulations, this stage is already considered a default event (see, e.g., the definitions of default in the US regulation implementing Basel II).

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<sup>6</sup>We exclude Chapter 7 and 15 filings, as these events represent less than 1% of all defaulted firms, which have outstanding traded corporate bonds. Furthermore, we find extremely infrequent trading activity for most of these bonds and, usually, no trading activity after the default event. This is not surprising as Chapter 7 filings are often used by small and medium-sized enterprises, which are not very active on the corporate bond market, and Chapter 15 is ancillary to a primary proceeding brought in another country, and not often applied, as domestic bankruptcy cases can be filed directly.

<sup>7</sup>Note that firms can be involved in multiple default events, as firms can default more than once in several years or because, e.g., defaults on payments can trigger multiple types of default events. To control for this possibility, we tested various alternative specifications in our empirical analysis, excluding overlapping events, e.g., using only the first default event per firm or employing only the most severe event. However, the qualitative nature of the results was very similar.

The second important data set we use is obtained from the TRACE database maintained by FINRA, which provides transaction information such as prices and volumes for the whole universe of US corporate bonds.<sup>8</sup> In the US corporate bond market, reporting to TRACE is obligatory for broker-dealers for all transactions, and follows a set of rules approved by the Securities and Exchange Commission (SEC), whereby all transactions must be reported within a time frame of 15 minutes. This data source is rather unique for an OTC market since, in almost all other cases, price information must usually be obtained either from an individual dealer’s trading book, which provides a very limited view of the market, or by using bid-ask quotations. We implement standard filters to exclude potential errors in TRACE.<sup>9</sup>

We match the default events with the transaction data of the individual bonds affected by the respective event, within the time window starting 90 days before default, and ending 90 days after the default event. However, some minimum requirements must be fulfilled in order for a bond to be included in our analysis. For each bond, we must observe at least 15 trades in each of the two time windows covering the periods of 90 days before and after default.<sup>10</sup> Also, we exclude from our sample bonds with an amount issued smaller than \$10 million, as well as bonds with complex structures, mostly related to embedded derivative features. The prices in default of bonds with such payoff structures may be quite different, and could potentially bias the analysis. In particular, therefore, we drop bonds that are rating-sensitive, convertible, sinkable, extendible, structured, or that possess any other kind of complex optionality. Thus, the bonds included in our analysis are either straight bonds, or simply puttable or callable.<sup>11</sup> Matching the TRACE data set with the default events results in 2,235 event/bond combinations (1,090 for nonfinancial firms and 1,145 for financial firms), covering 818 bonds issued by 259 firms, and accounting for approximately 1,734,000 trades, with an aggregate volume of \$500 billion.

We add bond data, firm characteristics, and macroeconomic data from Bloomberg, covering the amount issued, maturity, coupon, industry and seniority level, as well as interest rate information (US Federal Funds rate and Treasury yields), to assess the impact of overall economic conditions on the level of recovery rates. We match the data set with data from Markit, which enables the identification of bonds that can be delivered to settle CDS contracts following the default event.<sup>12</sup>

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<sup>8</sup>The reported trade volume is capped at \$1 million for high-yield and unrated bonds, and at \$5 million for investment-grade bonds. However, the exact trade volume is only released by FINRA after an 18-month delay.

<sup>9</sup>Dick-Nielsen (2009) provides an extensive description of possible reporting errors, and their implications for liquidity analysis. Such errors include (i) trade corrections within the same day, (ii) trade cancellations within the same day, and (iii) reversals across days, i.e., due to a mistake that was not detected on the trading day itself. Furthermore, we implement price filters, eliminating potentially erroneous reported prices.

<sup>10</sup>Note that we compared our results with a subsample of high trading activity bonds, i.e., with at least 25 trades, and confirmed that our results are not driven by very illiquid bonds with low trading activity.

<sup>11</sup>We assume that simple call and put options do not affect the analysis, as call options are deeply out-of-the-money in default, and put options offer no advantage as, basically, most default events trigger (cross-)acceleration clauses. Indeed, we confirmed this, repeating our analysis using only straight bonds and finding essentially the same results.

<sup>12</sup>Markit provides consensus valuations of CDS contracts across different maturities and restructuring clauses.

Furthermore, we retrieve detailed covenant information on our bonds from the Mergent Fixed Income Securities Database. In addition, we match the data set to balance sheet and income statement information obtained from Compustat. This permits us to analyze the effect of various balance sheet ratios, which are motivated by several models for recovery rates.

#### 4. Research questions and hypotheses

In this section, we discuss the research questions addressed and hypotheses tested in this paper. In particular, we consider the underlying trading activity in defaulted bonds and focus on the potential effects of bond characteristics, firm fundamentals, macroeconomic indicators, and liquidity measures on the level of recovery rates.

The microstructure of the trading activity in defaulted bonds allows us to analyze important research questions relating to how bond prices, trading volumes, and the number of trades evolve in different stages of default, and how a reliable market-based recovery rate can be estimated. We examine the trading activity in the defaulted bonds from 90 days before to 90 days after the observed default event date. In particular, we identify a “grace period” after the default event, during which prices are mainly driven by the effects of the default event itself, and test whether the trading activity levels are significantly different before and after this window. Furthermore, we examine the trading microstructure of various subsamples based on industry, rating, and default event type, and compare the trading activity in the defaulted bonds with that found in previous studies of non-defaulted bonds. In the analysis, it turns out that, in a grace period of 30 days following the default event, the trading activity is unique, indicating that the price evolution is mainly driven by the default event itself (see Section 6).<sup>13</sup>

In the main part of our analysis, we explore cross-sectional variations in these recovery rates along various dimensions. First, we focus on three aspects that have been found to be of importance in the previous literature: default event type, industry, and seniority. Starting with the default event type, we cover the full range of default events, from formal bankruptcy to informal unlikely-to-pay events. We test the hypothesis that formal statutory procedures are a sign of more severe economic problems within a firm and, thus, that bondholders are confronted with higher costs in this case than in the case of informal procedures. Therefore, we anticipate finding lower recoveries for Chapter 11 filings than for distressed exchanges and rating defaults. Furthermore, we expect default ratings to have lower recoveries than unlikely-to-pay ratings. As for industry affiliation, we would expect that, within *nonfinancial* industries, utility and energy firms should recover more than firms in other industries, as reported by various studies (see Section 2), due to their higher

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<sup>13</sup>Note that we also explore prices and price changes in later post-default periods to test whether our results depend on the particular time window chosen; see Section 6.4.

proportions of tangible assets. Similarly, among *financial* firms, commercial banks should recover more than investment banks, possibly because of their larger holdings of liquid assets. As for the seniority of the bonds, we hypothesize that, the greater the seniority and the collateral value of their assets, the higher will be the recovery rate.

Going beyond these simple dimensions, we analyze the effects of bond characteristics, firm fundamentals, macroeconomic variables, and liquidity variables on recovery rates. The potential effects of bond characteristics, such as amount issued, maturity, coupon, rating grade one year before default, CDS availability, and covenants (classified as investment, dividend, financing, and event-related restrictions), on recovery rates pose some interesting research questions. In particular, we conjecture that larger bond issues will recover more, as bonds with larger amounts issued are, in general, traded at higher prices (see, e.g., Friewald et al., 2012). We assume that bonds with longer maturities will recover less since long-term bonds are often held by buy-and-hold investors, such as insurance companies, and are often sold in large blocks upon default. We expect the coupon rate to be positively related to the recovery rate, since bonds with a higher coupon would be of higher value under certain outcomes of the default event. This would be the case if there was even a (small) positive likelihood of all contractual cash flows (including the higher coupon) being fulfilled after the default event, e.g., after a successful reorganization. Regarding the rating grade one year before default, we hypothesize that the lower is the rating grade, the lower will be the recovery rate. This is motivated by the idea that the rating grades of agencies might also reflect recovery risk. We expect to see a higher recovery rate if the bond is deliverable into a CDS contract, as this type of bond may generate greater demand from protection buyers upon default than would non-insurable bonds. Furthermore, we test whether covenants have an impact on the level of recovery rates. We hypothesize that bonds carrying covenants will exhibit higher recovery rates, as they might restrict firms from implementing certain policies, which could expose existing bondholders to higher risks, e.g., risky investment policies, higher payouts, changes in debt priority or control rights.

The characteristics of the firm will most certainly affect the level of the recovery rate. We assume that the value of equity and the default barrier will impact recoveries, as suggested by structural models of credit risk: The lower the market value of equity and the higher the default barrier, the lower will be the recovery of the debtholders, given a particular drop in the firm's asset value triggering default. Furthermore, we test whether earnings, tangible assets, receivables, and firm size positively affect the recovery rate.

Macroeconomic variables, such as market-wide default rates, industry-specific default rates, and information based on interest rate curves, are generally expected to have a significant impact on the level of recovery rates, as they are indicators of economic conditions. In particular, we hypothesize that high market-wide and industry-specific default rates signal that the economic

conditions are poor and, thus, could lead to lower recovery rates for individual firms. Similarly, when (short-term) interest rates are low, the economy will be at the lower end of the business cycle, with lower recovery rates. We also investigate the impact of the slope of the interest rate term structure on recoveries.

Furthermore, our detailed data set allows us, for the first time, to study the liquidity of defaulted bonds as an important additional aspect related to recovery risk. In particular, we estimate liquidity proxies, such as trading activity variables (volume and number of trades) and transaction cost measures (the Amihud measure and price dispersion measure), for the individual bonds, and test the hypothesis that less liquid bonds have lower recovery rates. We expect that the liquidity effects on prices that have been extensively documented in the literature on non-defaulted bonds (see, e.g., Bao et al., 2011; Dick-Nielsen et al., 2012; Friewald et al., 2012) will be exacerbated following default. In addition, we analyze whether changes in the liquidity measures can explain price changes between different post-default periods, assuming that the liquidity effects account for a significant proportion of the price evolution after default.

## 5. Methodology

This section outlines the general approach taken to measure the determinants of recovery rates in the US corporate bond market. We present, here, our definitions of the recovery rate and the various types of bond characteristics, firm fundamentals, macroeconomic variables and liquidity measures that are used to explain the bond recovery rate (see Section 4). We also present the regression setup that we use in our analysis.

### 5.1. Recovery rate

The recovery rate  $\pi$  of a bond  $i$ , issued by firm  $j$ , is defined in our analysis as the mean of the transaction prices  $p$ , per trade day and per \$100 of face value, across the default day  $t$  and the  $T = 30$  days after default.<sup>14</sup> If  $K_{i,j,s}$  is the number of trades of bond  $i$ , of firm  $j$ , on day  $s$ , indexed by  $k_{i,j,s}$ , then

$$\pi_{i,j,t} = \frac{1}{T+1} \sum_{s=t}^{t+T} \left( \frac{1}{K_{i,j,s}} \sum_{k_{i,j,s}} p_{s,k_{i,j,s}} \right). \quad (1)$$

Thus, this specification of the recovery rate suggests that the level of  $\pi_{i,j,t}$  can be interpreted as what an investor would have to pay or receive, on average, and hence in expectation, given that a default event has occurred, and given that the transaction takes place within the time

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<sup>14</sup>Additionally, we calculated the recovery of Treasury (instead of recovery of face value) for all our default event/bond combinations, so as to compare the results to the presented specification. In general, these alternative recovery rates are somewhat lower, as Treasury bond prices are often higher in crisis periods, when more defaults occur. However, the qualitative nature of our subsequent results is not affected and, thus, we do not present the results in detail.

window starting on the default day and ending 30 days after default. It should be noted that the accrued interest is set to zero, as most defaulted bonds are traded *flat*, i.e., without the exchange of accrued interest; thus, all prices under investigation are “clean” rather than “dirty.” The specification presented above represents a market-based definition of the recovery rate, in which a certain grace period is considered. We will further elaborate on our definition, based on the analysis of the trading microstructure in default, in Section 6.

## 5.2. Bond characteristics

We use a set of bond characteristics to explain differences in the recovery rates of corporate bonds. The most basic information available about a bond consists of its amount issued, maturity, and coupon. In addition, we consider the seniority level of the bond in question, which is, of course, very important when analyzing recovery rates. Specifically, we use four different levels of seniority: (i) guaranteed, (ii) secured, (iii) unsecured, and (iv) subordinated.<sup>15</sup>

Bond ratings from Fitch, Standard and Poor’s, and Moody’s, one year before the default events, are retrieved and mapped to natural numbers, i.e.,  $AAA = 1$ ,  $AA+ = 2$ ,  $\dots$ ,  $D = 21$ . With these data, we can analyze whether the rating grade *before* the default event is informative about the recovery rate. In other words, we can compare “expected” and “unexpected” credit events.

We collect information about whether the bond is deliverable into a CDS contract and, hence, is insurable in the CDS market. This is considered to be a bond-specific event, since only a selected list of bonds in a particular firm can be delivered into its CDS contract. For example, if, for a given firm, only CDS for unsecured debt are traded, then subordinated bonds cannot be insured.

Additionally, we analyze the effect of bond covenants on recovery rates. We retrieve detailed covenant information for our entire sample of bonds from the Mergent Fixed Income Securities Database, containing 54 different restrictions in the bond indenture contracts. We follow the approach taken by Chava et al. (2010) to group bond covenants into four main categories (investment, dividend, financing, and event), relying on the framework provided by Smith and Warner (1979). The rationale for the grouping is based on the nature of the restriction imposed by the particular covenant. A bond is classified as carrying an *investment covenant*, if it contains restrictions on investments, e.g., risky investments, mergers and acquisitions, or asset sales, while a *dividend covenant* implies restrictions on payments to shareholders. A *financing covenant* restricts policies on debt (stock) issuances, debt priority, or defines minimum (respectively, maximum) limits regarding earnings or indebtedness. Finally, an *event covenant* contains a change in control clause, such as a poison put.

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<sup>15</sup>Note that, for some bonds, the financial data vendors provide more granular classifications of seniority. However, the four classes listed above are important and relevant for all bonds, with such data generally being available for almost all bonds.

### 5.3. Firm fundamentals

We employ certain firm characteristics in our analysis. First, we use the industry in which the firm operates as an important characteristic. Second, we use balance sheet and income statement information as explanatory variables; these are available for the fiscal year *prior to* the default event. We use the following six accounting ratios, which are directly motivated by structural credit risk models (see Section 2):

$$\text{Equity} = \frac{\text{Market value of equity}}{\text{Total assets}} \quad (2)$$

$$\text{Default barrier} = \frac{\text{Short-term debt} + \frac{1}{2}\text{Long-term debt}}{\text{Total assets}} \quad (3)$$

$$\text{LTD issuance} = \frac{\text{Long-term debt}}{\text{Total debt}} \quad (4)$$

$$\text{Profitability} = \frac{\text{EBITDA}}{\text{Total sales}} \quad (5)$$

$$\text{Intangibility} = \frac{\text{Intangible assets}}{\text{Total assets}} \quad (6)$$

$$\text{Receivables} = \frac{\text{Total receivables}}{\text{Total assets}} \quad (7)$$

We use the value of *equity* over total assets as a general indicator of the financial condition of the firm.<sup>16</sup> The value of equity is used in many structural credit risk models to infer the asset value of the company and also to define the leverage. Furthermore, we use the *default barrier* as defined by Moody’s Analytics (previously known as Moody’s KMV), which is widely used in structural credit risk modeling, i.e., in assessing the *distance to default* measure of firms. In addition, we define *LTD issuance* as the ratio of long-term debt to total debt, since long-term debt is regarded as a more stable funding source, and less likely to cause default in the short run.<sup>17</sup> We measure *profitability* using the earnings before interest, taxes, depreciation, and amortization (EBITDA), motivated by structural models based on cash flows. In addition, we analyze *intangible* assets and *receivables* over total assets. Finally, we use total assets and number of employees as size proxies for firms.<sup>18</sup>

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<sup>16</sup>In a few cases, we replaced the market value of equity with the book value of equity, when reliable data were not available for the former.

<sup>17</sup>Note that we also analyzed the debt structure of the firm based on the debt priority, i.e., we measured the percentages of secured, unsecured, and subordinated debt. However, these debt structure variables turned out to be insignificant in our analysis and, therefore, are not presented in detail here.

<sup>18</sup>Note that many of these characteristics are regularly used in credit scoring models as well, e.g., in Altman’s Z-Score model (see Altman, 1968).

#### 5.4. Macroeconomic variables

We consider four different macroeconomic indicators: the market-wide default rate, the industry-specific default rate, the Federal Funds rate, and the slope of the term structure of interest rates. The market-wide default rate is an indicator of overall financial distress in the corporate bond market, while the industry-specific default rate is an indicator of industry-wide distress (see also Acharya et al., 2007). The Federal Funds rate and the slope of the term structure are indicators of the state of the business cycle. We define the default rate, for a default event at time  $t$ , as the ratio of defaulted bonds to total outstanding bonds, in the whole US corporate bond market, or in the respective industry, in the time interval from  $T = 90$  days before day  $t$  to day  $t$ .

$$\text{Default rate}_t = \frac{\text{Defaulted bonds}_{t,t-T}}{\text{Outstanding bonds}_{t,t-T}}. \quad (8)$$

In addition, we consider the Federal Funds rate on the default event day as the relevant short-term interest rate, to avoid issues of default risk and illiquidity, particularly after the financial crisis. We define the slope of the yield curve on the default event day as the difference between the Federal Funds rate and the ten-year US Treasury yield.<sup>19</sup>

#### 5.5. Liquidity proxies

We define various liquidity proxies, which we use as additional explanatory variables. We employ simple trading activity variables, e.g., the volume and number of trades, and more sophisticated liquidity measures, e.g., the Amihud and price dispersion measures, which have been used in the literature (see, e.g., Dick-Nielsen et al., 2012; Friewald et al., 2012). We estimate these measures in the time window from the default day  $t$  to  $T = 30$  days after  $t$ .

##### *Volume*

The volume variable,  $v_{i,j,t}$ , is the average transaction volume per trading day, of bond  $i$  of firm  $j$ , across the period from the default day  $t$  to  $T = 30$  days after  $t$ :

$$v_{i,j,t} = \frac{1}{T+1} \sum_{s=t}^{t+T} \left( \frac{1}{K_{i,j,s}} \sum_{k_{i,j,s}} v_{s,k_{i,j,s}} \right). \quad (9)$$

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<sup>19</sup>We tried using alternative measures of the short-term interest rate, such as the Treasury bill yield and the London Interbank Offered Rate (Libor), and the slope of the term structure as explanatory variables. However, the results were basically similar, and here we report only the results of using the definitions given above.

### *Number of trades*

This variable,  $n_{i,j,t}$ , is the average number of trades of bond  $i$  of firm  $j$ , per trading day, across the period from the default day  $t$  to  $T = 30$  days after  $t$ :

$$n_{i,j,t} = \frac{1}{T+1} \sum_{s=t}^{t+T} K_{i,j,s}. \quad (10)$$

### *Amihud measure*

The Amihud measure (see Amihud, 2002) measure of bond  $i$  of firm  $j$ , on day  $s$ , given  $N_{i,j,s}$  observed returns  $r$  on this day indexed by  $k_{i,j,s}$ , is defined as:

$$\text{Amihud}_{i,j,s} = \frac{1}{N_{i,j,s}} \sum_{k_{i,j,s}} \frac{|r_{k_{i,j,s}}|}{v_{k_{i,j,s}}}. \quad (11)$$

We use the average Amihud measure across the period from the default day to 30 days thereafter in our analysis. This measure, based on Kyle (1985), and originally designed for limit order markets, assesses the price impact of the traded volume, and hence the depth of the market. Intuitively, a market is considered illiquid if a low transaction volume causes relatively large price changes.

### *Price dispersion measure*

Similarly to Jankowitsch et al. (2011) and Friewald et al. (2012), we define the price dispersion,  $d_{i,j,s}$ , of bond  $i$  of firm  $j$  on day  $s$  as:

$$d_{i,j,s} = \sqrt{\frac{1}{\sum_{k_{i,j,s}} v_{k_{i,j,s}}} \cdot \sum_{k_{i,j,s}} \left( \frac{p_{k_{i,j,s}}}{m_{i,j,s}} - 1 \right)^2 \cdot v_{k_{i,j,s}}}, \quad (12)$$

where  $m_{i,j,s}$  is the mean transaction price, representing the fair value of the bond, and  $p_{i,j,s}$  are the individual trade prices. The (volume-weighted) volatility of the individual trades around the fair value permits a direct estimation of transaction costs based on transaction data. We use the average price dispersion measure across the period from the default day to 30 days thereafter in our analysis. The intuition behind this measure is motivated by market microstructure models: A low dispersion of traded prices around its market-wide valuation indicates that the bond can be bought or sold close to its fair value and, thus, at a lower transaction cost, indicative of a more liquid instrument.

### *5.6. Pooled regression model*

We rely on a pooled regression approach to analyze the determinants of recovery rates in the US corporate bond market. Motivated by the discussion in the previous section, the recovery rate  $\pi$  of bond  $i$  issued by firm  $j$ , given default on day  $t$ , is assumed to be given by:

$$\begin{aligned}
\pi_{i,j,t} = & \alpha + \beta \cdot (\text{Bond characteristics})_{i,j} + \gamma \cdot (\text{Firm fundamentals})_{j,t-1} & (13) \\
& + \phi \cdot (\text{Macroeconomic indicators})_t + \delta \cdot (\text{Liquidity})_{i,t} \\
& + \lambda \cdot (\text{Default event type})_{i,j,t} + \mu \cdot (\text{Industry})_j \\
& + \zeta \cdot (\text{Seniority})_{i,j} + \epsilon_{i,j,t}.
\end{aligned}$$

Thus, this specification combines the entire time-series and the cross-section of recovery rates. We use ordinary least squares regressions, adjusting the standard errors for the existence of default event clusters across firms, as described in Williams (2000) and Petersen (2009). This approach addresses the issue that, in a particular default event, a firm may have several bonds outstanding, and that all these defaulted bonds will show up as separate observations in our data.<sup>20</sup> In addition, all our regressions include the default event, industry, and seniority dummy variables.

## 6. Results

### 6.1. Descriptive analysis

This section studies the underlying trading activity in defaulted bonds in the US corporate bond market and presents descriptive statistics for the resulting recovery rates. We first explore the traded prices and volumes on the default day, and in the 90-day windows before and after default. Focusing on the recovery rate itself, we analyze its empirical distribution and quantify the effects of the default event type, industry, and seniority on recovery rates. We also document the variation in recovery rates over time. In addition, we provide summary statistics for the explanatory variables that are used in the various regression specifications.

#### *Trading microstructure of defaulted bonds*

In this section, we examine the underlying trading activity in defaulted bonds. Fig. 1 provides the evolution of the mean transaction prices per day as a percentage of face value, for a time window starting 90 days before and ending 90 days after the default event day, across all default event/bond combinations. In addition, the mean number of trades and trading volume in defaulted bonds per day are presented. Investigating the transaction prices of all defaulted bonds, we find that the lowest price is observed on the default day itself, and is around 35% of face value. The price level 90 days before default is already low, and shows a declining trend from about 57% to 45%. However, the default event day witnesses a significant drop in price and is, thus, apparently

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<sup>20</sup>As robustness checks, we repeated our analysis using only one (randomly selected) bond per event and using only non-overlapping events (either employing only the first of overlapping events or the most severe event). We basically obtained similar results (not presented in detail in the paper).

not fully anticipated by the market. Interestingly, we find that the transaction price recovers steadily to 42%, in the ensuing 30 days after default, whereas, after 30 days, the price shows a less volatile evolution. Using the Kolmogorov-Smirnov test, we find that the transaction prices within the 90-day window before default are significantly different from those on the default day itself, and in the subsequent 30 days, which are, in turn, significantly different from those in the time frame from 31 to 90 days after default.<sup>21</sup>

The analysis of the mean number of trades and traded volume across all default event/bond combinations exhibits interesting patterns. In particular, the average number of trades per bond on the default day, of around 35, is significantly higher than on all other days. This number of trades is also remarkably high compared to the market-wide average across the whole corporate bond market of 3 to 4 trades per day per bond (see, e.g., Friewald et al., 2012). The number of trades decreases rapidly in the 30 days after default, to around 8 to 10 trades per day per bond, which is still higher than the market-wide average. The average daily traded volume per bond is around \$10 million on the default day, and decreases to the same extent as the number of trades, to about \$3 million. Again, the traded volume on the default day is higher than the market-wide average of around \$5 million (see, e.g., Friewald et al., 2012).<sup>22</sup> As in the case of the transaction prices, the Kolmogorov-Smirnov test reveals the statistical significance of the presented differences.

Overall, we document the lowest prices and highest levels of trading on the default day. The price recovers steadily over the next 30 days, with a continuing active market for the bonds. Thus, this finding provides strong evidence that the price evolution in this time window of zero to 30 days is mainly driven by the reactions of market participants to the default event itself, as the trading activity is significantly higher than in the pre-default and later post-default windows. Given the low prices following default, at least for some bonds, the increased trading activity is not a sign of increased liquidity per se, but rather evidence of sell-side pressure.<sup>23</sup> The following rationale might explain this pattern: On the one hand, this effect might be driven by some investors having particular needs to trade at these default prices, e.g., because they immediately have to liquidate their positions due to mandate restrictions or binding risk limits. Furthermore, the evolution of the trading volume suggests that it is necessary to split up and sell larger positions in defaulted bonds over time.<sup>24</sup> On the other hand, trading activity in this window might be stimulated by

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<sup>21</sup>Note that this result is not triggered by different sets of bonds that are traded before and after default, as we define a minimum level of trading activity in both time windows, as described in Section 3.

<sup>22</sup>We also quantified the average trading activity in the defaulted bonds between issuance and the start of our time windows, based on TRACE data, and found that the number of trades and traded volume were in line with the market-wide averages for these periods.

<sup>23</sup>Note that we observe this pattern in roughly 70% of all default event/bond combinations and, thus, it is not driven by a few events with strong price movements. Therefore, postponing the selling activities might be worthwhile for investors trading marginal volumes (see Section 6.4 for a discussion).

<sup>24</sup>Indeed, practitioners we spoke to confirmed that trading a large volume in a defaulted bond often makes it necessary to be active in the market for several days due to the price impact of individual trades.

investors' heterogeneous beliefs concerning the implications of the default event for the value of the firm's assets. Based on these findings, we define the recovery rate in our analysis as the mean transaction price in the window between the default date and 30 days after default. Thus, this specification can be interpreted as the price, on average and hence in expectation, resulting from trading in this time window. We consider this definition of a market-based recovery rate more reliable and relevant for investors than quotations or last-trade information drawn from the default date alone, which have been used by many prior studies due to data limitations that existed before the detailed TRACE data became available. This significant methodological distinction makes our subsequent analysis all the more robust.

Fig. 1 further investigates the trading activity among four important subgroups: for *nonfinancial* versus *financial* bonds, and *investment-* versus *speculative-*grade bonds, we again analyze the mean transaction prices, the number of trades, and traded volumes in the 90 days before and 90 days after the default event. The general patterns observed in the previous analysis of the full sample are confirmed in each subgroup: First, the lowest transaction price is reported on the default day itself. Second, trading activity is especially high on the default day and gradually declines after that. When comparing nonfinancial and financial firms, we find that, for nonfinancial firms, the price decline leading towards the default day is smoother, and the price drop on the default day itself is less severe (from 43% to 35%, compared to 47% to 33% for financials), indicating that the actual default is more of a surprise to the market in the case of financial firms. For both groups, the number of trades and the traded volume are especially high on the default day. In addition, the general level of trading activity around the default date seems to be higher for financial firms than for nonfinancial firms, possibly on account of the surprise. For example, the mean number of trades is around 22 for nonfinancial firms, compared to around 70 for financial firms, on the default day. The comparison of investment- versus speculative-grade bonds also yields interesting insights. While the mean transaction prices for speculative-grade bonds decline gradually as default approaches, prices drop rather steeply on the default day in the case of investment-grade bonds (from 42% to 35% for the former, compared to 47% to 27% for the latter). This may, again, indicate a greater surprise element in the case of default for the more creditworthy investment-grade bonds. The number of trades and traded volumes are higher for investment-grade bonds, as expected.

Fig. 2 presents mean transaction prices from 90 days before to 90 days after default for the different default event types.<sup>25</sup> Transaction prices for Chapter 11 liquidation and restructuring filings exhibit very similar patterns. In both cases, the default event induces a relatively sharp

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<sup>25</sup>The analyses of the traded volumes and number of trades for different default event types yield very similar results to the previous analyses and are, therefore, not presented, in the interests of conserving space.

decline in prices on that date itself, from about 50% to 25%. Within the first 30 days after default, prices recover to around 40%. Especially interesting is the analysis of mean transaction prices in the case of distressed exchanges. The pattern reveals that these cases are the only default events for which transaction prices before default are lower than after default, indicating that the default itself is seen as a sign of relief by the market, after an uncertain negotiation process. In particular, distressed exchanges exhibit the highest transaction prices in the post-event phase. For rating-based default events, we find that unlikely-to-pay announcement events by all rating agencies lead to a sharp drop in prices, indicating an element of surprise, whereas the event of downgrading to an actual default rating class seems to be generally anticipated by the market.

#### *Recovery rates and effects of event type, industry, and seniority*

Analyzing the resulting recovery rates, i.e., the mean transaction prices across the period from the default day to 30 days after default, we first present the empirical distribution of the recovery rates of defaulted US corporate bonds between 2002 and 2010, in Fig. 3. The mean recovery rate is equal to 38.6% with a standard deviation of 27.4%. While the mean recovery rate is close to the 40% estimate provided by Altman and Kishore (1996), which is widely used in academia and industry, the standard deviation around this number suggests substantial variation in recovery rates across different dimensions; therefore, a comprehensive analysis of the driving factors is important. Specifically, three peaks can be identified in the empirical distribution: one up to 20%, one between 40% and 50%, and one between 60% and 70%. The lowest peak is mainly driven by the recovery rates of bonds issued by Lehman Brothers, which traded at about 15% after it filed for protection under Chapter 11 on September 15, 2008. The defaulted bonds of CIT Group and Washington Mutual contribute to the other two peaks. Overall, the distribution documents the stochastic nature of the recovery rate.

Fig. 4 displays the time-series of mean recovery rates in the US corporate bond market as a quarterly moving average. We find that recovery rates are highly volatile over time: around 60% in 2007, compared to 20% at the end of 2008. Not surprisingly, the lowest mean recovery rates can be found during the financial crisis. Thus, cross-sectional average recovery rates are clearly not constant over time.

We present summary statistics in Table 2, displaying the recovery rates across different default event types, industries, and seniority levels in order to analyze the important determinants of recovery rates. In total, we report 2,235 default event/bond combinations for which transaction data are available. Panel A displays the statistics for the overall sample and confirms the results discussed when presenting the empirical distribution. Panel B displays recovery rates across different default event types. Chapter 11 restructuring filings form the largest group, consisting of 492 observations, whereas we observe only 13 Chapter 11 liquidations. Interestingly, we find

only an insignificant difference between the mean recovery rates of Chapter 11 restructuring and liquidation filings (i.e., 37.1% vs. 40.7%). Distressed exchanges exhibit, on average, the highest recovery rate of 51.3%, confirming that default events not relying on formal bankruptcy procedures have significantly higher recovery rates, potentially as a result of preserving more of the “going concern” value for bondholders. Furthermore, we find significant differences in recovery rates when analyzing the default grades of the rating agencies. We find, within the Fitch and Moody’s credit classifications, that the actual default grade has a significantly lower recovery rate than the unlikely-to-pay grade (Fitch: 31.4% vs. 41.3%; Moody’s: 16.0% vs. 44.9%). This difference is pronounced, especially in the case of Moody’s, indicating that its rating framework is indeed more sensitive to the expected loss. For Standard and Poor’s, such a difference is not observable, which could indicate that Standard and Poor’s does not incorporate recovery aspects, as suggested by its rating framework.<sup>26</sup>

Panel C displays recovery rates across *nonfinancial* industries, while Panel D reports recovery rates for *financial firms*. One should note that our sample is fairly balanced between nonfinancial and financial firms (1,090 observations belong to nonfinancial firms, while 1,145 belong to financial firms). We find that, among nonfinancial industries, utility and energy firms recover, on average, the most (e.g., *electricity* 48% and *oil & gas* 44.4%), while retail firms recover the least at 33.4%. Among financial industries, we find that the overall highest recovery rate of 56.6% is reported for the *credit & financing* industry, while the *financial services* industry exhibits the lowest recovery rates; this result is mainly driven by the low recoveries of Lehman Brothers debt. The averages across financial firms (38.8%) and nonfinancial firms (38.5%) are almost identical, while the standard deviations are high in every industry group.

Panel E displays the average recovery rates across seniority levels. As expected, secured bonds recover, on average, the most (around 49.3%), while bonds that are subordinated recover, on average, the least (around 15.1%). Interestingly, we find only a small difference in recovery rates between guaranteed (40.3%) and unsecured bonds (39.1%). This could be the result of guarantees being provided to the bonds of subsidiaries by the holding company, making the guarantees worthless in the case of the default of the holding company.

#### *Summary statistics of the explanatory variables*

The previous analysis shows a pattern of significant cross-sectional and time-series variation in recovery rates, which we may be able to explain using a more detailed analysis of a comprehensive set of explanatory variables. Table 3 reports the summary statistics for the main explanatory variables in our empirical analysis for the *full* sample and separately for *nonfinancial* firms and

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<sup>26</sup>Moody’s Investors Service (2002), Standard & Poor’s (2011), and FitchRatings (2013) provide the relevant information concerning the three rating frameworks.

*financial* firms, covering bond characteristics, firm fundamentals, and liquidity proxies. We first discuss the results for the full sample, and then highlight the differences between nonfinancial and financial firms.

Panel A of Table 3 summarizes the results for the bond characteristics: The average issue size of defaulted bonds is \$400 million. The average maturity and coupon rate are 6.82 years and 7.48%, respectively. The average bond rating one year before default is BB, i.e., most of the defaulting bonds are from the speculative grades. All these variables show considerable variation. For example, the standard deviation of the credit rating is five notches. More than 80% of the bonds are deliverable into a CDS contract. Analyzing the four covenant categories, we find that approximately half of the bonds are encumbered by an investment, financing, and event covenant, while one-third of the bonds carry a dividend covenant. Interestingly, Table 3 shows that, for financial firms, the average bond rating is A– (investment grade), while for nonfinancial firms, the average bond rating is B– (speculative grade), indicating that the default of a financial firm is often not considered very likely by rating agencies one year before the actual event, whereas, for nonfinancial firms, the economic situation of the company is already perceived as weak one year prior to default. A similar difference, with parallel reasoning, can be found for the coupon rate (financial firms: 5.8% vs. nonfinancial firms: 8.6%). Furthermore, defaulted financial bonds have, on average, a longer maturity by about 2.5 years. In line with previous literature (see, e.g., Chava et al., 2010), covenants are more common among nonfinancial than financial firms.

Panel B in Table 3 presents the statistics for firm fundamentals. On average, firms have an equity ratio of 6.6% of total assets. The average default barrier equals 47.8% of total assets. Comparing financial and nonfinancial firms, we find that there is only a small difference between the equity ratios of these two groups. Interestingly, the default barrier is higher for financial firms (around 53%) than for nonfinancial firms (around 23%), indicating that the former use more short-term financing. On average, receivables are 50% of total assets for financial firms, but only 10% for nonfinancial firms. There is also a huge gap between the two groups of firms in terms of the intangibility of assets: For nonfinancial firms, intangibility is ten times as high as it is for financial firms. Analyzing the size proxies, in the whole sample, the average firm size (in terms of total assets) is equal to \$139 billion, with 2,970 employees.<sup>27</sup> While the average firm size of defaulted financial firms is ten times that of nonfinancial firms, the latter have 2.2 times as many employees as the former.

Panel C summarizes the trading activity variables and liquidity measures. The trading activity variables confirm that the number of trades and trading volume are above the market-wide average. Interestingly, bonds of financial firms have, on average, five trades more per day than nonfinancial

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<sup>27</sup>The average firm size is skewed by a few large financial firms.

firms. However, the volume per trade is much lower (around \$260,000 vs. \$470,000). Analyzing the liquidity measures, we find that trading in defaulted bonds generates relatively high transaction costs. Thus, defaulted bonds are extremely illiquid in this sense. The average price impact given by the Amihud measure of a \$1 million transaction is 1.49%, while the market-wide average is at 0.36%; similarly, the average transaction cost, estimated by the price dispersion measure, amounts to 2.80%, which is six times as high as the overall market average of 0.43% (for comparison, see Friewald et al., 2012).

Fig. 5 provides time-series evidence regarding the key macroeconomic variables, i.e., the market-wide default rate, the Federal Funds rate and the 10-year Treasury rate (used in the slope variable). Studying the market-wide default rate, three regimes can be identified: the “*dot-com*” bubble in 2002 and 2003, the Ford and General Motors crisis in 2005, and the financial crisis in 2008 and 2009.<sup>28</sup> The period during the financial crisis saw the highest market-wide quarterly default rate, of around 3.6%. We find a significant variation in default rates during our observation period, allowing us to analyze the relation between recovery and default rates.<sup>29</sup> The Federal Funds rate shows similar patterns, but in the opposite direction, i.e., low rates in the crisis periods, and high rates in the boom phases. The difference between the 10-year Treasury rate and the Federal Funds rate, is large at the end of a crisis, and low or negative at the beginning of a crisis period, whereas the 10-year rate itself is rather stable over time, albeit with a decrease since the financial crisis, due to central bank intervention in the form of quantitative easing.

## 6.2. Regression models explaining recovery rates

In this section, we present the results of the various regression models explaining the variation in the recovery rates of corporate bonds. The recovery rates are explained by bond characteristics, firm fundamentals, macroeconomic variables, and liquidity proxies, as well as dummy variables for the default event types, industries, and seniority classes.<sup>30</sup> Table 4 presents six different regression specifications.<sup>31</sup> Model 1 represents a regression including only the dummy variables for the default event types, industries, and seniority levels. This specification can be used as a benchmark against which we explore the increases in explanatory power of the other specifications.

<sup>28</sup>See Friewald et al. (2012) for a related analysis on the different regimes in the US corporate bond market.

<sup>29</sup>Note that we do not present individual time-series for the industry-specific default rates, in the interest of conserving space. However, most industries have high default rates during the financial crisis, whereas between 2002 and 2007, there are more pronounced differences in the default rates across industries.

<sup>30</sup>In addition, we performed a factor analysis and identified five factors representing a *balance sheet factor*, a *size factor*, a *macroeconomic factor*, a *trading activity factor*, and a *transaction costs factor*, and then ran the regressions afresh based on these factors to avoid potential multicollinearity. The results based on these factors confirm the overall findings (sign and significance) and are, thus, not presented in detail.

<sup>31</sup>Note that we additionally employed treatment-effects and Heckman (1979) procedures, respectively, in order to address potential self-selection of firms into either formal bankruptcy procedures or out-of-court default events, as applied in Bris et al. (2006) and Davydenko and Franks (2008) in the context of recovery rates. We find in all our specifications insignificant Inverse-Mills ratios and, moreover, the results remain unchanged when we employ the self-selection procedures (similar findings are reported in the related literature). Therefore, we do not report the results in detail.

We find an adjusted  $R^2$  of 37% for Model 1. This shows reasonable explanatory power even for this specification. Thus, important dimensions are already included and the results of the descriptive analysis are confirmed. The next four specifications, Models 2 to 5, control for each of the four defined groups of variables, i.e., bond characteristics, firm fundamentals, macroeconomic variables, and liquidity proxies, respectively. We find that all four groups add to the explanation of recovery rates. Bond characteristics (Model 2) increase the adjusted  $R^2$  by six percentage points to 43%. However, these characteristics are not as important as those in the other groups. Firm fundamentals (Model 3) and macroeconomic variables (Model 4) seem to be of similar importance, exhibiting adjusted  $R^2$  values of 47% and 48%, respectively. We obtain the highest adjusted  $R^2$  of 53% by including liquidity measures (Model 5). Thus, the trading activity and transaction cost measures are important additional variables, necessary in explaining recovery rates.

Model 6 in Table 4 includes all four sets of variables. We focus on this complete model to discuss the effects of the individual variables. We find that this model is able to capture 66% of the variation in recovery rates. Among the bond characteristics, six variables turn out to be significant. We find that bonds with a longer maturity exhibit lower recoveries, i.e., an increase in the time to maturity by one year decreases the recovery rate by around 0.6% of face value. This effect might be caused by sell-side pressure imposed by large institutional investors such as insurance companies, which typically hold bonds with a longer time to maturity but may be forced to sell following default due to mandate restrictions. Furthermore, we find a small positive effect for the coupon rate, potentially indicating that bonds with a higher coupon are of higher value under certain outcomes of the default event. This effect indicates a (small) positive likelihood that the contractual cash flows of the bond (including the higher coupon) may actually still be paid even after the default event. The rating variable is significant; i.e., the rating one year before the default event conveys information concerning the recovery rate. A one-rating-notch difference is associated with a 1.1% difference in the recovery rate. An interesting result is provided by the CDS dummy that indicates whether a bond can be delivered into a CDS contract. In particular, we find that bonds that are deliverable into a CDS contract exhibit around 6.2% higher recovery rates of face value than bonds that are non-deliverable. This effect is quite significant in economic terms, and may arise due to a possible increase in demand from protection buyers, who are obliged to deliver certain bonds to protection sellers in the case of default. Regarding the four different covenant groups, the results reveal that, first, bonds that carry investment covenants exhibit higher recoveries (around 4.4% of face value), and second, bonds that exhibit financing covenants recover up to 9.7% more of their face value, which is a strong economic effect. Thus, restrictions on the investment and financing policy are an effective tool by which creditors can increase their recovery rates.

Among the firm characteristics, we find significant effects for the ratios motivated by structural

credit risk models, i.e., the higher is the equity value and the lower is the default barrier, the higher is the recovery rate. In particular, the partial net effects of these two ratios are roughly similar, while the economic impacts differ. That is, an increase in the equity ratio and a decrease in the default barrier by ten percentage points increase the recovery rate by around 1.3% and 2.2%, respectively. In addition, we find marginally significant effects for receivables and firm size. The other firm characteristics employed (long-term debt issuance, intangibility, receivables, profitability, and employees) are statistically insignificant in the joint model. Thus, the information from these characteristics may already be contained in the industry dummies.

The third group of explanatory variables are macroeconomic characteristics, of which the two most important variables are the market-wide and industry-specific default rates. Several studies (see, e.g., Altman et al., 2002) conclude that aggregate default rates and aggregate recovery rates are negatively associated. Moreover, Acharya et al. (2007) find that industries in distress experience lower recovery rates. As already mentioned in Section 5, we employ more precise estimates of the default rates; based on the default event date, we derive, for each recovery rate, a market-wide as well as an industry-specific default rate in a trailing 90-day window, so as to measure the contemporaneous interaction effect between default rates and recovery rates. In addition, we consider the Federal Funds rate on the default event date as the relevant short-term rate and we explore the slope between the 10-year Treasury rate and this short-term interest rate. All four variables are highly statistically significant. In particular, we find that high default rates (market-wide as well as industry-specific) and low short-term interest rates imply lower recoveries. For example, an increase in the market-wide and industry-specific default rate by one percentage point lead to a decrease in recoveries by around 3.3% and 0.7%, respectively. In addition, we find a positive effect of the slope factor; i.e., in regimes that could be associated with higher optimism, we observe higher recoveries. Overall, as expected, poor economic conditions result in lower recovery rates as systematic risk factors influence the level of recoveries.

The fourth group of explanatory variables consists of the liquidity measures (volume, number of trades, Amihud measure, and price dispersion measure). We find that liquidity effects are of particular importance in explaining the variation in recovery rates across different bonds in default. In particular, the price dispersion measure is highly significant and exhibits a negative coefficient, indicating that illiquid bonds suffer more of a decline in the event of default than liquid bonds. In particular, we find that an increase in the price dispersion measure by 100 basis points leads to a decrease in recovery rates by around 5.0%.<sup>32</sup> The volume and number of trades variables turn out

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<sup>32</sup>Note that our result concerning the impact of liquidity on the recovery rate does not depend on the use of the price dispersion measure. We tested other measures, e.g., the Roll measure, and found similar effects. However, the price dispersion measure appears to be more suitable in the case of defaulted bonds, for which we observe a large number of small trades. Whereas the price dispersion measure uses a low weight for these observations, some of the other measures give a particularly high weight to low-volume transactions, thus exaggerating their relative

to be insignificant, indicating that higher trading activity after default is more a sign of sell-side pressure, at least for some bonds, than of increased liquidity.

Overall, we find important factors to be driving the recovery rates of corporate bonds following default. As expected, bond characteristics have the lowest explanatory power. However, we document the strong economic effect of deliverability into CDS contracts and bond covenants on the recovery rate. On the other hand, firm characteristics motivated by structural credit risk models, and macroeconomic variables, are clearly linked to recovery rates. Interestingly, liquidity variables, especially those proxies that measure transaction costs, are significant factors in explaining recovery rates.<sup>33</sup>

### 6.3. *Subsample analysis for nonfinancial and speculative-grade bonds*

In this section, we present the results for two important subsamples of our data set, i.e., nonfinancial and speculative-grade bonds. This analysis allows us to validate the results of the previous section, and to analyze whether certain results could be driven by financial firms (especially Lehman Brothers) or by large investment-grade firms. Table 5 provides the results for nonfinancial (Model 1) and speculative-grade bonds (Model 2). We find an adjusted  $R^2$  of 55% for both subsamples. Analyzing the effects of the individual variables, we find similar results to those for the overall sample; all groups of characteristics add to the explanatory power, with most variables that are significant in the overall model being so again for the subsamples. Thus, the main results stay much the same for these two subsamples.

However, some interesting differences can be highlighted, in particular, among the bond characteristics for the CDS delivery and bond covenant variables. The option to deliver the bond into a CDS contract reveals the following insights in the two subsamples: While, for *nonfinancial* bonds, the possibility of delivering the bond into a CDS contract produces a similar effect to that observed in the overall sample, we find a weaker effect for *speculative-grade* bonds, perhaps indicating that many CDS positions in these bonds are closed before an expected default event. Concerning the bond covenants, we find that financing restrictions are important determinants of recovery rates for both subsamples, while the other covenants are of minor importance, indicating that protection against changes in the debt structure and minimum standards for the repayment capacity provide higher recovery rates.

As for firm characteristics, we find similar results in the subsample regressions as in the overall sample. Interestingly, the partial effects of equity and the default barrier become stronger for both of these groups, compared to the full sample. In addition, receivables and the number of

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importance.

<sup>33</sup>This implication of low liquidity of defaulted bonds has been recently discussed theoretically by He and Milbradt (2013), who incorporate liquidity effects immediately after default in their credit risk model.

employees seem to matter for nonfinancial and speculative-grade bonds; e.g., an increase in the number of employees by 1,000 leads to an increase in recoveries by around 0.5% of face value for these two groups.

The significance and directional effects of the macroeconomic variables remain basically unchanged in the subsamples compared to the full sample. However, further interesting insights can be obtained from the liquidity measures. For the transaction cost measures (both Amihud and price dispersion metrics), we find results similar to those for the full sample. However, the effect of the price dispersion measure is more pronounced in these two subsets. An increase in transaction costs by 100 basis points is associated with a decrease in recoveries by 7.5% to 8.8%, indicating that illiquidity effects are of particular importance for nonfinancial and speculative-grade bonds in explaining the variation in bond recoveries.

#### 6.4. Analysis of price changes following the recovery rate window

In this section, we compare the presented recovery rates covering the traded prices on the default day and the following 30 days (i.e., the recovery rate window), to the traded prices in a later post-default period represented by the time window from 31 to 90 days following default. Thus, we explore the potential effect on our results of the temporary price pressure observed directly after default. In particular, this comparison allows us to address the question of whether the cross-sectional determinants of post-default traded prices are influenced by the specific time window chosen. In addition, we study to what extent observed price changes between the two time windows can be explained by changes in the underlying liquidity.

For this comparison, we quantify the average traded price for each bond/event combination in the time window from 31 to 90 days after default. As already indicated by Fig. 1 and discussed in Section 6.1, the average traded price in this time window (41.6%) is significantly higher than in the time window from zero to 30 days after default (38.6%), as temporary sell-side pressure, at least for some bonds, arises directly after default. Thus, investors selling average quantities can expect a 3% higher recovery rate with respect to the face value of the bond. As indicated by Fig. 2, this increase is mainly observed for distressed exchanges and unlikely-to-pay events, whereas there are no significant changes for formal bankruptcy procedures. Examining the price movements of different industries, this increase can be found for most industries, with *oil & gas* and *electricity* exhibiting a particularly strong increase of around 5% of face value. Concerning the bond seniorities, for unsecured, guaranteed, and secured bonds we find the indicated average price increase, whereas the prices of subordinated bonds stay at much the same level throughout the 90 days following default.<sup>34</sup>

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<sup>34</sup>Note that, to conserve space, the results concerning prices in the time window from 31 to 90 days following default with respect to industries and seniorities are not presented in detail.

Given the observed differences between these two time windows in terms of average traded prices, it is important to explore whether these changes only affect the general level of prices or significantly influence the previously presented effects of the cross-sectional determinants too. To address this question, we repeat the regression analysis, using the average traded prices in the time window from 31 to 90 days after default as the dependent variable. We also adjust the liquidity measures accordingly. The results are given in Table 5, Model 3. We find an adjusted  $R^2$  of 66%, meaning that the explanatory power of the determinants is basically identical to when we use the time window from zero to 30 days after default. In addition, the signs and significance levels of the individual variables correspond well to the original specification. The only relevant exception, and the most interesting difference between the specifications, is that trading activity variables (volume and number of trades) are additional significant variables explaining prices in the time window from 31 to 90 days after default. Both variables enter with a positive sign; i.e., higher trading activity corresponds to higher levels of liquidity and, thus, higher price levels. Analyzing the economic significance, a one standard deviation change in trading volume is related to a price differential of 2.3% of face value; correspondingly, for the number of trades, a one standard deviation change relates to a price differential of 2.1%. Thus, we find that, in later post-default periods, the trading activity variables explain cross-sectional price differences. Such a relation cannot be found directly after default since, for at least some bonds, an increase in trading activity is not a sign of increased liquidity, but rather of severe sell-side pressure. Examining the transaction cost variables, we find that the Amihud measure is significant in this specification as well; a one standard deviation change corresponds to a 2.7% change in price levels.

The coefficients of the liquidity variables provide interesting implications in general: Note that, as already discussed, we observe significantly higher trading activity in the time period from zero to 30 days following default, combined with lower prices. However, if we were to assume, for a specific bond, a similar level of trading activity as is observed directly after default occurring in the time window from 31 to 90 days following default, then the presented results suggest that a significant price impact would emerge. This impact would presumably decrease the price level to the range observed in the recovery rate window. Thus, the investors cannot simply shift their trading activity from directly after default to the later period as similar price pressure effects would occur, as the depth of the market is still thin in the period 31 to 90 days following default.

Thus, overall, the presented variables consistently explain prices within the first 90 days after default, with the individual effects remaining roughly at the same level between the recovery rate window and the period from 31 to 90 days after default. The only important difference between the two time windows is that liquidity measures based on trading activity provide cross-sectional explanatory power after effects induced by temporary sell-side pressure cease, and higher trading activity indeed signals higher liquidity for a given bond.

Therefore, in order to further elaborate on the importance of liquidity at different stages following default, we study the relation between changes in the liquidity measures and the traded prices. As a first step, we compare the liquidity measures observed in the two different time windows (see Table 6 Panel A). The number of trades is on average 10.7 in the recovery rate window compared to 5.7 in the later period with the mean volume per trade being \$360,000 compared to \$345,000. Addressing the transaction cost metrics, the price impact of trading \$1 million amounts to 1.5%, as given by the Amihud measure compared to 0.9% in the later period, while the mean price dispersion measure is 2.8% compared to 2.4%. Thus, we observe considerable differences in the liquidity measures; however, we find that trading in defaulted bonds in the window from 31 to 90 days after default still results in relatively high transaction costs.

Given the observed differences, we explore how the evolution in the underlying liquidity is related to the price changes, employing an additional regression analysis. Table 6 Panel B displays five different models, with the dependent variable given by the change in the average traded price between the recovery rate window and the time window of 31 to 90 days after default, and the explanatory variables represented by the changes in the liquidity measures between these two windows (additionally, the models contain dummies for the default event type, industry, and seniority). Models 1 to 4 control for each of the liquidity measures, in turn, while Model 5 contains the full model. Overall, we find that all liquidity variables turn out to be significant with the expected sign when included individually (see Models 1 to 4). Focusing on the full model (Model 5), we find an adjusted  $R^2$  of 23%. Three liquidity measures are significant – the two trading activity variables (volume and number of trades) and the price dispersion measure. Volume and trades enter with a positive sign, indicating that bonds for which trading activity remains high after the recovery rate window experience a stronger price increase compared to bonds for which trading activity returns to lower levels. In particular, for a one standard deviation change in volume (number of trades), prices increase by as much as 0.4% (0.7%) of face value. Bonds for which transaction costs decrease by more, after the recovery rate window has ended, experience significantly higher price increases. Thus, a one standard deviation decrease in the price dispersion measure increases prices by 1.5% of face value. Overall, the presented results reveal that liquidity effects account for an economically significant portion of the price formation in default, when compared to the average price increase of 3% of face value between these two windows.

## 7. Conclusion

The recovery rate in the event of default is an important risk factor in pricing financial contracts exposed to credit risk. Many defaults in the recent past have highlighted the stochastic nature of recovery rates for corporate bonds. Therefore, it is important to understand the determinants of this risk factor in greater detail. In this paper, we examine the recovery rates of defaulted US

corporate bonds, based on a complete set of transaction data over the time period from 2002 to 2010. In particular, we investigate the underlying microstructure of trading activity for a broad set of default event types covering formal bankruptcy procedures, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events. This analysis allows us to provide reliable market-based estimates of the recovery rates, quantify liquidity effects and, hence, study price formation for individual defaulted bonds, an innovation relative to the prior literature. Our research focus is on the relation between these recovery rates and a comprehensive set of bond characteristics, firm fundamentals, macroeconomic variables, and liquidity measures.

Studying the microstructure of the trading activity reveals that the lowest bond prices indeed occur on the default event day itself (around 35% of face value, on average). Interestingly, trading activity on this day, measured by volume and number of trades, is quite high in comparison with non-defaulted bonds. The prices recover to around 42% in the following 30 days after default, with the trading activity still remaining high, indicating temporary price pressure following a default event. Thereafter, trading activity dies down to pre-default levels. Based on these findings, we define the market-based recovery rate of a defaulted bond as the average traded price over the default day and the following 30 days.

The subsequent regression analysis explains 66% of the total variation in recovery rates, employing bond characteristics, firm fundamentals, macroeconomic variables, and liquidity measures as explanatory variables. We find that transaction cost metrics measuring liquidity are particularly important variables. Considering the other characteristics, we show that bond covenants restricting firms' investment (respectively, financing) policies, balance sheet ratios motivated by structural credit risk models, and macroeconomic conditions are significant factors. As expected, we confirm that the type of default event, the industry in which the firm operates, and the seniority of the bond, are of importance. Additional evidence for the importance of liquidity effects is provided by exploring price changes observed at different stages following default.

In summary, we provide a comprehensive analysis offering detailed insights into the trading microstructure of defaulted bonds as well as into the stochastic nature of recovery rates, and quantify the effects of various endogenous and exogenous factors on these recovery rates. Our results will be of interest to both academics and practitioners in relation to pricing corporate bonds, managing bond portfolio risk, and setting capital adequacy standards for financial institutions.

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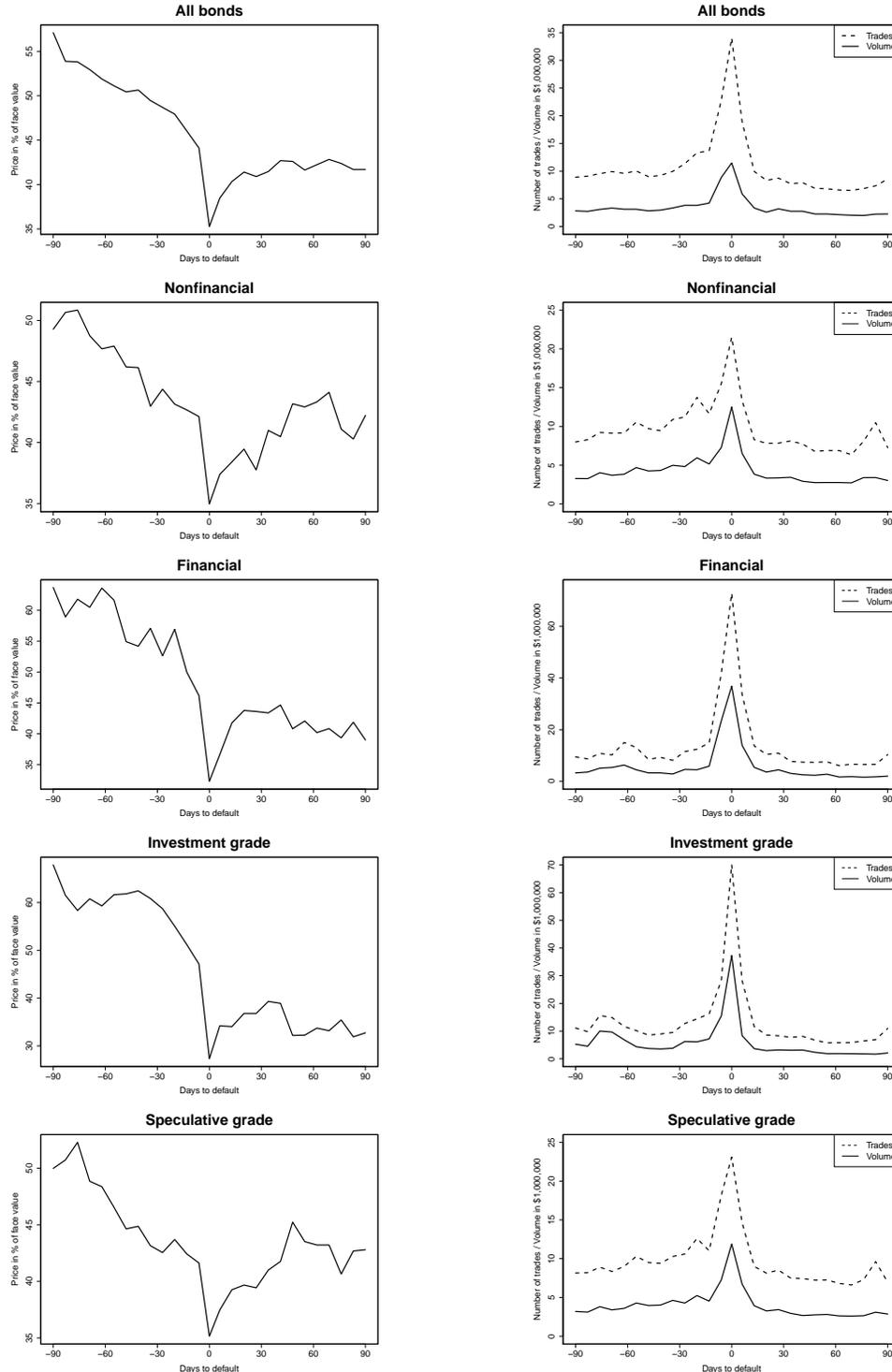
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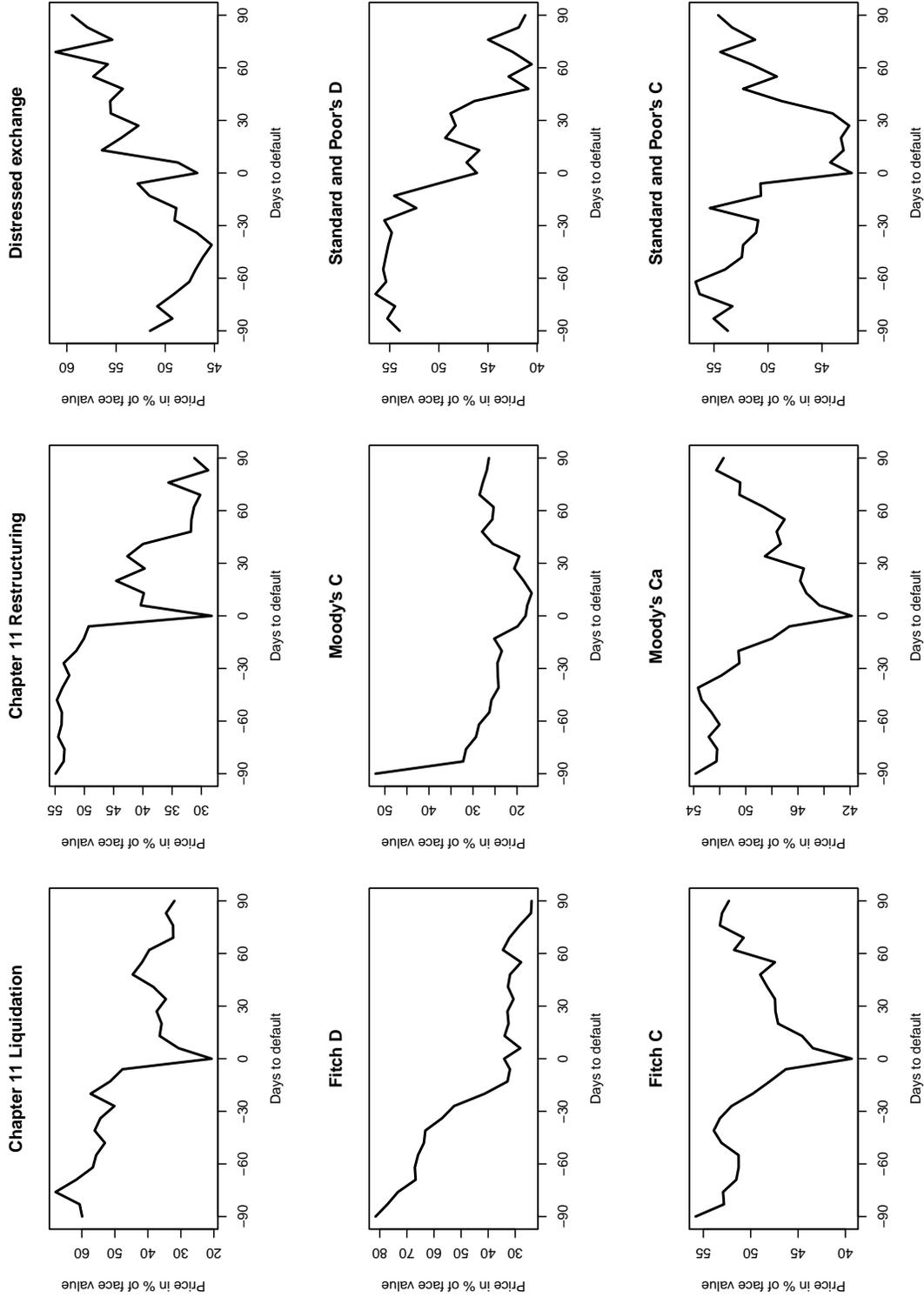
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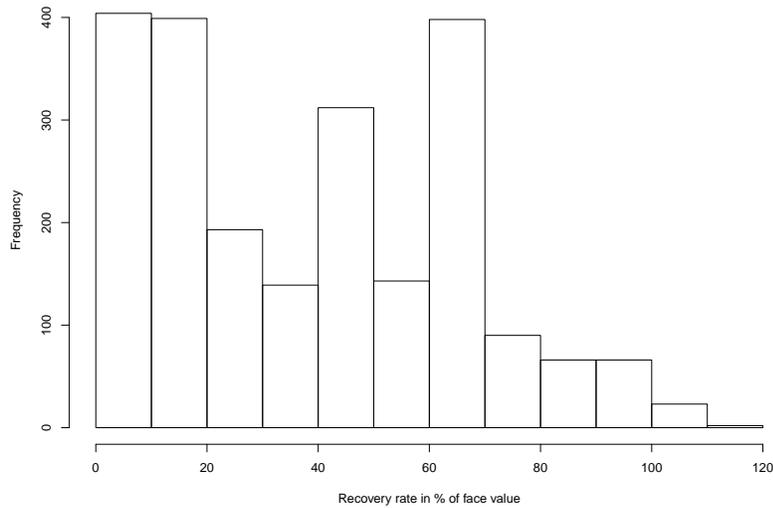
**Fig. 1.** This figure shows mean transaction prices and volumes, as well as the average number of trades per bond, on the default day and in the time window from 90 days before to 90 days after default, for the sample of *all* bonds, for *nonfinancial* and *financial* bonds, as well as for *investment*- and *speculative*-grade bonds. The left side of the figure displays transaction prices, while the right side of the figure displays trading activity. The data set consists of transaction data reported by TRACE for the period from July 2002 to October 2010 and amounts to approximately 1,734,000 trades with an aggregate volume of \$500 billion covering 2,235 default event/bond combinations. The default events were obtained from the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database and cover bankruptcy filings, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events.



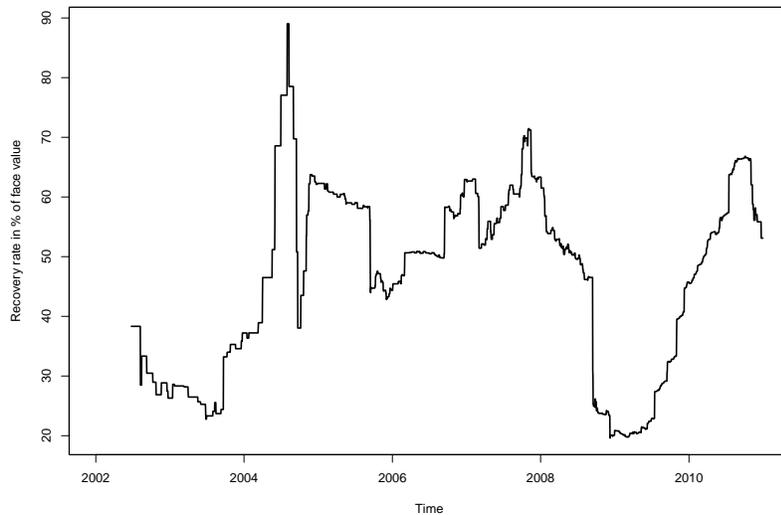
**Fig. 2.** This figure shows mean transaction prices across the different default event types on the time window from 90 days before to 90 days after default. The data set consists of transaction data reported by TRACE for the period from July 2002 to October 2010 and amounts to approximately 1,734,000 trades with an aggregate volume of \$500 billion covering 2,235 default event/bond combinations. The default event data were obtained from the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database and cover bankruptcy filings, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events.



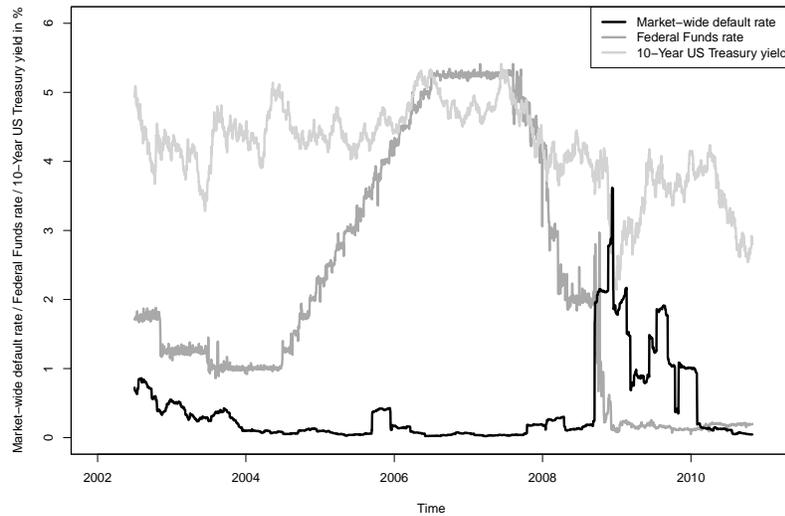
**Fig. 3.** This figure shows the empirical distribution of recovery rates of defaulted US corporate bonds. Recovery rates are defined as the average traded price per bond over the default day and the following 30 days after default. The data set consists of transaction data reported by TRACE for the period from July 2002 to October 2010 and amounts to approximately 1,734,000 trades with an aggregate volume of \$500 billion covering 2,235 default event/bond combinations. The default events data were obtained from the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database and cover bankruptcy filings, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events.



**Fig. 4.** This figure shows the time-series of mean recovery rates (quarterly moving average) in the US corporate bond market. Recovery rates are defined as the average traded price per bond over the default day and the following 30 days after default. The data set consists of transaction data reported by TRACE for the period from July 2002 to October 2010 and amounts to approximately 1,734,000 trades with an aggregate volume of \$500 billion covering 2,235 default event/bond combinations. The default events data were obtained from the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database and cover bankruptcy filings, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events.



**Fig. 5.** This figure shows the time-series of the market-wide default rate in a 90-day trailing window, which is defined as the corresponding fraction of defaulted bonds and outstanding bonds in the whole US corporate bond market, the Federal Funds rate, and the ten-year US Treasury yield for the time period from July 2002 to October 2010. The data set consists of transaction data reported by TRACE for the period from July 2002 to October 2010 and amounts to approximately 1,734,000 trades with an aggregate volume of \$500 billion covering 2,235 default event/bond combinations. The default events data were obtained from the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database and cover bankruptcy filings, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events. The Federal Funds rate and the Treasury yield were retrieved from Bloomberg.



**Table 1** This table lists the different default event types used in the analysis and their definitions. We consider three classes of default events: filings for protection under Chapter 11 (restructuring and liquidation), distressed exchanges, and rating downgrades from the three major rating agencies, i.e., Fitch, Moody's and Standard and Poor's, representing payment defaults and unlikely-to-pay events. The default events data were obtained from the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database.

Type	Description
Chapter 11 liquidation	If a business is unable to service its debt or pay its creditors, either the business itself or any of its creditors can file with a federal bankruptcy court for protection under Chapter 11. As the <i>debtor in possession</i> , the trustee may liquidate the assets of the firm.
Chapter 11 restructuring	If a business is unable to service its debt or pay its creditors, either the business itself or any of its creditors can file with a federal bankruptcy court for protection under Chapter 11. As the <i>debtor in possession</i> , the trustee may restructure the firm.
Distressed exchange	Debtor proposes a fundamental change in the contractual commitments to creditors, who may voluntarily agree to it.
Fitch D	Rating grade indicates that firm has entered default.
Moody's C	Obligations rated C are the lowest rated class and are typically in default, with little prospect for recovery of principal or interest.
Standard & Poor's D	Payment default on financial commitments.
Fitch C	Substantial credit risk. Default is a real possibility.
Moody's Ca	Obligations rated Ca are highly speculative and are likely in, or very near, default, with some prospect of recovery of principal and interest.
Standard & Poor's C	Currently highly vulnerable obligations.

**Table 2**

This table reports the summary statistics for the recovery rates (average traded price per bond over the default day and the following 30 days after default) across different default event types, industries, and seniority levels. We report the lowest recovery rate (Min), 25% quantile ( $Q_{0.25}$ ), median, mean, 75% quantile ( $Q_{0.75}$ ), highest recovery rate (Max), standard deviation (SD), and number of observations (N). Panel A provides the statistics for the total sample, Panel B lists the summary statistics for recovery rates across the different default event types, Panel C presents the statistics for *nonfinancial* firms, and Panel D for *financial* firms. Panel E gives the statistics for recoveries across different levels of seniority. The data set consists of transaction data reported by TRACE for the period from July 2002 to October 2010 and amounts to approximately 1,734,000 trades with an aggregate volume of \$500 billion covering 2,235 default event/bond combinations. The default events data were obtained from the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database and cover bankruptcy filings, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events. The industry classifications and seniority levels (secured, guaranteed, unsecured, subordinated) were retrieved from Bloomberg.

	Min	$Q_{0.25}$	Median	Mean	$Q_{0.75}$	Max	SD	N
<i>Panel A: All recovery rates</i>								
All	0.01	12.89	38.53	38.61	65.41	116.50	27.36	2,235
<i>Panel B: Recovery rates across default event types</i>								
Chapter 11 liquidation	0.12	11.61	23.13	40.68	69.44	103.60	39.32	13
Chapter 11 restructuring	0.01	11.24	25.96	37.11	65.78	110.80	28.76	492
Distressed exchange	10.65	28.98	51.04	51.26	72.35	98.71	25.46	64
Fitch D	0.41	8.22	26.06	31.36	60.44	63.70	25.54	24
Moody's C	0.01	3.10	8.47	16.02	23.87	100.00	19.03	289
Standard & Poor's D	0.01	13.99	47.85	43.84	66.01	109.10	27.43	465
Fitch C	0.29	18.11	43.43	41.28	55.23	116.50	25.21	361
Moody's Ca	0.26	24.97	43.61	44.87	59.28	109.10	23.87	456
Standard & Poor's C	0.55	21.45	38.53	43.59	65.93	110.00	28.11	71
<i>Panel C: Recovery rates by industry: nonfinancial firms</i>								
Manufacturing	0.01	13.52	31.03	38.93	64.36	110.80	28.55	573
Media & Communications	0.01	4.32	21.06	34.70	66.85	101.00	34.56	163
Oil & Gas	9.85	33.74	41.67	44.37	53.63	92.79	23.68	21
Electricity	23.81	35.71	40.07	48.03	48.04	102.80	22.67	39
Retail	1.41	6.66	16.35	33.40	57.88	100.50	34.19	33
Service & Leisure	0.03	13.49	26.99	38.65	63.98	116.50	30.37	190
Transportation	16.78	25.74	26.94	38.17	57.46	78.38	18.85	70
Real Estate	13.56	34.29	40.63	41.97	49.01	95.97	16.05	71
<i>Panel D: Recovery rates by industry: financial firms</i>								
Banking	14.32	21.98	59.54	49.26	61.27	69.50	20.19	62
Credit & Financing	2.26	43.79	65.38	56.58	66.01	98.01	14.28	588
Financial services	0.01	4.91	9.87	10.64	13.81	98.63	9.75	363
Insurance	7.96	12.22	34.66	43.37	73.99	96.14	32.72	17
Savings & Loan	0.01	0.37	0.69	10.74	28.49	30.25	13.41	44
<i>Panel E: Recovery rates by seniority</i>								
Secured	0.03	9.89	43.17	49.27	87.98	110.00	37.47	84
Guaranteed	0.01	16.90	34.73	40.27	63.43	116.50	28.13	585
Unsecured	0.14	12.90	42.39	39.09	65.56	101.00	25.69	1,457
Subordinated	0.01	0.58	5.31	15.13	17.86	98.71	23.79	109

**Table 3**

This table reports the summary statistics of bond characteristics (Panel A), firm fundamentals (Panel B), and liquidity proxies (Panel C) for *all* firms as well as for *nonfinancial* firms and *financial* firms. We report the mean, standard deviation (SD), and number of observations (N). Amount issued is given in millions, maturity in years, coupon as a percentage of notional, and ratings are mapped to natural numbers, e.g., AAA = 1, AA+ = 2, ..., D = 21. Bond covenants and CDS availability are represented by dummy variables. Equity, default barrier, intangibility, and receivables are given as a percentage of total assets, LTD issuance as a percentage of total debt, and profitability as a percentage of total sales. Total assets are given in \$100 billions, employees in multiples of 1,000, and volume in multiples of \$100,000. The Amihud measure represents a price change in percentage terms, based on \$1 million of volume, and price dispersion is given as a percentage. The data set consists of transaction data, reported by TRACE for the period from July 2002 to October 2010 and amounts to approximately 1,734,000 trades with an aggregate volume of \$500 billion covering 2,235 default event/bond combinations. The default events data were obtained from the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database and cover bankruptcy filings, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events. Bond characteristics were retrieved from Bloomberg and the Mergent Fixed Income Securities Database, the firm fundamentals from Compustat.

	All			Nonfinancial firms			Financial firms		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
<i>Panel A: Bond characteristics</i>									
Amount issued	399.60	517.80	2,235	434.80	459.40	1,090	366.00	565.90	1,145
Maturity	6.82	6.62	2,235	5.57	5.07	1,090	7.97	7.64	1,145
Coupon	7.48	2.35	2,235	8.63	1.99	1,090	5.77	1.73	1,145
Rating	12.21	5.15	2,235	16.78	2.04	1,090	7.86	3.00	1,145
CDS availability	83.31	—	2,235	97.82	—	1,090	68.07	—	1,145
Investment covenant	56.42	—	2,235	92.20	—	1,090	22.36	—	1,145
Dividend covenant	32.93	—	2,235	62.75	—	1,090	4.54	—	1,145
Financing covenant	53.29	—	2,235	90.46	—	1,090	17.90	—	1,145
Event covenant	47.52	—	2,235	80.09	—	1,090	16.51	—	1,145
<i>Panel B: Firm fundamentals</i>									
Equity	6.62	21.26	2,164	6.59	30.56	1,023	6.65	4.46	1,141
Default barrier	47.80	25.14	2,181	23.37	17.70	1,040	53.02	15.11	1,141
LTD issuance	24.14	30.58	2,117	21.58	28.76	979	26.35	31.91	1,138
Intangibility	11.60	19.01	2,180	22.07	22.57	1,042	2.01	5.76	1,138
Receivables	31.28	26.52	2,140	10.26	9.83	999	49.68	22.57	1,141
Profitability	37.47	29.15	2,133	12.93	15.44	1,040	60.83	17.70	1,093
Total assets	1.39	1.84	2,184	0.23	0.65	1,043	2.45	1.94	1,141
Employees	2.97	5.29	2,158	4.16	7.08	1,024	1.89	2.37	1,134
<i>Panel C: Liquidity proxies</i>									
Volume	3.60	3.61	2,235	4.67	2.97	1,090	2.58	3.86	1,145
Trades	10.71	16.57	2,235	8.20	11.67	1,090	13.09	19.87	1,145
Amihud	1.49	1.84	2,024	1.36	1.91	953	1.61	1.77	1,071
Price dispersion	2.80	1.98	2,024	2.48	1.73	953	3.09	2.15	1,071

**Table 4**

This table reports the results of the various regression specifications. The dependent variable is the recovery rate of the default event/bond combinations. The explanatory variables are given by bond characteristics (amount issued, maturity, coupon, rating, and dummies for CDS availability as well as investment, dividend, financing, and event covenant), firm characteristics (equity, default barrier, LTD issuance, intangibility, receivables, profitability, total assets, and employees), macroeconomic variables (market-wide default rate, industry-specific default rate, Federal Funds rate and slope of the interest rate curve), liquidity proxies (volume, number of trades, Amihud measure, and price dispersion measure), and dummy variables representing default event types, industries, and seniority levels. Model 1 represents a regression including only these dummy variables. Model 2 additionally controls for the bond characteristics. Model 3 controls for the firm characteristics. Model 4 controls for the macroeconomic indicators and Model 5 controls for the liquidity proxies. Model 6 represents the complete model containing all variables. The data set consists of transaction data reported by TRACE for the period from July 2002 to October 2010 and amounts to approximately 1,734,000 trades with an aggregate volume of \$500 billion covering 2,235 default event/bond combinations. The default events data were obtained from the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database and cover bankruptcy filings, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events. Bond characteristics and macroeconomic data were retrieved from Bloomberg and the Mergent Fixed Income Securities Database, the firm fundamentals from Compustat. Clustered standard errors at the default-event/firm level (see, e.g., Petersen, 2009) are given in parentheses. Significance is indicated by: \*\*\* < 0.01, \*\* < 0.05, \* < 0.1.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	36.5099*** (1.7535)	57.9068*** (5.8240)	32.3022*** (4.9439)	30.6604*** (5.3943)	50.5939*** (2.0104)	13.1919 (11.4184)
Amount issued		-0.2760 (0.1895)				0.6603 (0.8613)
Maturity		-0.6359*** (0.0641)				-0.6164*** (0.0631)
Coupon		0.5176* (0.2803)				0.7089** (0.3139)
Rating		-1.5283*** (0.3275)				-1.0579*** (0.3836)
CDS availability		0.8345 (1.8968)				6.1844*** (2.0805)
Investment covenant		4.8720** (2.0599)				4.4075** (1.9355)
Dividend covenant		8.0674*** (1.9915)				-1.7356 (2.1808)
Financing covenant		7.8911*** (2.1692)				9.7090*** (2.0492)
Event covenant		-1.7631 (2.0517)				-2.5204 (1.8549)
Equity			0.1603*** (0.0573)			0.1279*** (0.0526)
Default barrier			-0.2523*** (0.0758)			-0.2175*** (0.0649)
LTD issuance			-0.1124*** (0.0269)			-0.0029 (0.0285)
Intangibility			-0.2401*** (0.0571)			-0.0587 (0.0467)
Receivables			0.2465*** (0.0824)			0.1638* (0.0865)
Profitability			0.0044 (0.0627)			-0.0642 (0.0546)
Total assets			1.5252 (1.1822)			2.1414* (1.1302)
Employees			-0.5454*** (0.1829)			0.0839 (0.1742)
Market default rate				-4.1092*** (1.0208)		-3.3428*** (1.1457)
Industry default rate				-0.8631*** (0.1186)		-0.6561*** (0.1068)
Federal Funds rate				12.1875*** (1.2165)		7.0241*** (1.4479)
Slope				13.3993*** (1.4790)		7.4729*** (1.6254)
Volume					0.0955 (0.1814)	0.0785 (0.2183)
Trades					0.1299*** (0.0263)	0.0140 (0.0212)
Amihud					-0.0790 (0.2730)	0.0797 (0.3125)
Price dispersion					-5.6500*** (0.2900)	-4.9700*** (0.3300)
Adjusted $R^2$	0.37	0.43	0.47	0.48	0.53	0.66
Observations	2,235	2,235	1,972	2,235	2,024	1,809
Event dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Seniority dummies	Yes	Yes	Yes	Yes	Yes	Yes

**Table 5**

This table reports the results for three additional regression analyses. The explanatory variables are given by bond characteristics (amount issued, maturity, coupon, rating, and dummies for CDS availability as well as investment, dividend, financing, and event covenant), firm characteristics (equity, default barrier, LTD issuance, intangibility, receivables, profitability, total assets, and employees), macroeconomic variables (market-wide default rate, industry-specific default rate, Federal Funds rate, and slope of the interest rate curve), liquidity proxies (volume, number of trades, Amihud measure, and price dispersion measure), and dummy variables representing default event types, industries, and seniority levels. In Model 1 (*nonfinancial* firms) and Model 2 (*speculative-grade* firms), the dependent variable is the recovery rate of the default event/bond combinations. Model 3 contains results for an *alternative period*, where the dependent variable is represented by the average traded price per default event/bond combination in the time window from 31 to 90 days after default. The data set consists of transaction data reported by TRACE for the period from July 2002 to October 2010 and amounts to approximately 1,734,000 trades with an aggregate volume of \$500 billion covering 2,235 default event/bond combinations. The default events data were obtained from the Mergent Fixed Income Securities Database and the NYU Salomon Center Master Default Database and cover bankruptcy filings, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events. Bond characteristics and macroeconomic data were retrieved from Bloomberg and the Mergent Fixed Income Securities Database, the firm fundamentals from Compustat. Clustered standard errors at the default-event/firm level (see, e.g., Petersen, 2009) are given in parentheses. Significance is indicated by: \*\*\* < 0.01, \*\* < 0.05, \* < 0.1.

Model	(1. Nonfinancial)	(2. Speculative-grade)	(3. Alternative period)
Intercept	17.7210 (14.3467)	26.5738** (13.4267)	8.2693 (11.9746)
Amount issued	0.0802 (0.1817)	0.7805 (1.4907)	-0.3090 (0.9779)
Maturity	-1.0338*** (0.1456)	-1.0109*** (0.1540)	-0.5651*** (0.0686)
Coupon	0.8776* (0.5096)	0.8604* (0.4624)	0.6193* (0.3221)
Rating	-1.3604*** (0.4760)	-1.4200*** (0.5058)	-0.6355* (0.3045)
CDS availability	6.4090*** (2.1291)	4.6294** (2.3320)	9.5436*** (2.1993)
Investment covenant	3.0832 (3.0816)	2.6558 (2.4154)	2.5636 (1.9154)
Dividend covenant	-0.2918 (2.3326)	-1.2639 (2.4444)	-2.9496 (2.2888)
Financing covenant	8.8260*** (3.3200)	9.4359*** (2.9599)	7.9240*** (2.1733)
Event covenant	-6.4800 (3.4527)	-5.2612 (3.3698)	-0.3426 (1.9737)
Equity	0.2133*** (0.0534)	0.1765*** (0.0499)	0.1109*** (0.0406)
Default barrier	-0.3074*** (0.0662)	-0.2586*** (0.0623)	-0.2303*** (0.0737)
LTD issuance	0.0337 (0.0299)	0.0247 (0.0295)	-0.0014 (0.0253)
Intangibility	-0.0315 (0.0489)	-0.0177 (0.0451)	-0.1476*** (0.0506)
Receivables	0.2128** (0.1075)	0.1739* (0.0985)	0.2227*** (0.0832)
Profitability	-0.0708 (0.0627)	-0.0657 (0.0551)	-0.0043 (0.0476)
Total assets	1.8437 (1.4994)	0.9190 (1.1199)	3.8492** (1.7977)
Employees	0.5521** (0.2277)	0.4976*** (0.1764)	-0.1429 (0.1997)
Market default rate	-4.0621*** (1.4929)	-4.4021*** (1.4145)	-3.7935*** (1.2655)
Industry default rate	-0.7298*** (0.1931)	-0.6808*** (0.1893)	-0.8425*** (0.1244)
Federal Funds rate	9.1806*** (1.7549)	7.6705*** (1.5492)	4.9011*** (1.5064)
Slope	10.4349*** (1.9991)	8.5255*** (1.6764)	6.8276*** (1.7156)
Volume	-0.4264 (0.3652)	-0.2598 (0.3420)	0.7466*** (0.2537)
Trades	0.0959 (0.0689)	0.1424** (0.0612)	0.3490*** (0.0763)
Amihud	-0.3920 (0.4886)	-0.6708 (0.4419)	-0.8614*** (0.1292)
Price dispersion	-8.8340*** (0.5500)	-7.5300*** (0.7200)	-5.4874*** (0.3840)
Adjusted $R^2$	0.55	0.55	0.66
Observations	795	868	1,780
Event dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
Seniority dummies	Yes	Yes	Yes

**Table 6**

This table reports the results analyzing changes in prices and liquidity between the time window starting on the default day and ending 30 days after default, and the time window from 31 to 90 days after default. Panel A presents the summary statistics, mean, and standard deviation (SD), of the changes in liquidity proxies (volume, number of trades, Amihud measure, and price dispersion measure) between these two time windows for *all* firms as well as for *nonfinancial* and *financial* firms. Volume is measured in multiples of \$100,000, the Amihud measure represents a price change in percentage terms, based on \$1 million of volume, and the price dispersion measure is given as a percentage. Panel B provides the regression models, with the dependent variable given by the change in mean transaction prices of all default event/bond combinations between these two time windows. The explanatory variables are the changes in the liquidity measures between these two time windows, and dummy variables representing default event types, industries, and seniority levels. Model 1 contains the results for changes in volume, Model 2 for changes in trades, Model 3 for changes in the Amihud measure, Model 4 for changes in the price dispersion measure, and Model 5 for changes in all liquidity measures. The data set consists of transaction data reported by TRACE for the period from July 2002 to October 2010 and amounts to approximately 1,734,000 trades with an aggregate volume of \$500 billion covering 2,235 default event/bond combinations. The default events data were obtained from the Merger Fixed Income Securities Database and the NYU Salomon Center Master Default Database and cover bankruptcy filings, out-of-court restructurings, and downgrades to default status by rating agencies representing payment defaults and unlikely-to-pay events. Bond characteristics were retrieved from Bloomberg. Clustered standard errors at the default-event/firm level (see, e.g., Petersen, 2009) are given in parentheses. Significance is indicated by: \*\*\* < 0.01, \*\* < 0.05, \* < 0.1.

	<i>Panel A: Changes in liquidity proxies</i>									
	All		Nonfinancial firms			Financial firms				
	Mean	SD	Mean	SD	Mean	SD	Mean	SD		
$\Delta$ Volume	-0.15	1.77	-0.18	2.09	-0.12	1.41				
$\Delta$ Trades	-4.98	10.76	-2.74	8.01	-7.08	12.45				
$\Delta$ Amihud	-0.63	1.78	-0.97	1.75	-0.38	1.82				
$\Delta$ Price dispersion	-0.46	1.63	-0.26	1.43	-0.64	1.77				
<i>Panel B: Models</i>										
	(1)	(2)	(3)	(4)	(5)					
Intercept	-0.4004 (0.4855)	-0.3913 (0.4847)	-0.3306 (0.5044)	-0.3328 (0.4914)	-0.2154 (0.4903)					
$\Delta$ Volume	0.2796*** (0.1040)				0.2389* (0.1313)					
$\Delta$ Trades		0.0446*** (0.0128)			0.0606*** (0.0123)					
$\Delta$ Amihud			-0.3162*** (0.0989)		0.0142 (0.1059)					
$\Delta$ Price dispersion				-0.8431*** (0.1045)	-0.9025*** (0.1140)					
Adjusted $R^2$	0.20	0.20	0.20	0.22	0.23					
Observations	1,780	1,780	1,780	1,780	1,780					
Event dummies	Yes	Yes	Yes	Yes	Yes					
Industry dummies	Yes	Yes	Yes	Yes	Yes					
Seniority dummies	Yes	Yes	Yes	Yes	Yes					