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Labor Risk and Corporate Credit Spreads: The Expected Recovery Rate Channel

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Labor Risk and Corporate Credit Spreads

The Expected Recovery Rate Channel

A dissertation submitted in partial satisfaction

of the requirements for the degree Doctor of Philosophy

in Management

by

Zhipeng Li

2018

ABSTRACT OF THE DISSERTATION

Labor Risk and Corporate Credit Spreads

The Expected Recovery Rate Channel

by

Zhipeng Li

Doctor of Philosophy in Management

University of California, Los Angeles, 2018

Professor Andrea Lynn Eisfeldt, Chair

Intangible capital embodied in the firm's key employees has become an increasingly important factor of production. Potential separation of employees upon default reduces the expected remaining value of the firm's asset. Therefore, investors should expect lower recovery rates and require higher bond spreads for labor-intensive firms. I construct a market-based proxy for firm-level recovery rates and show that recovery rate variations are an important determinant of bond spreads. Then I find firms with relatively higher labor shares have lower average recovery rates and higher spreads through quasi-experiments.

The dissertation of Zhipeng Li is approved.

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1 Introduction

Intangible capital that relies on essential human inputs has become an increasingly important factor of production. The distinguishing feature of such intangible capital is that it is partly embodied in labor inputs. As a result, potential separation of key personnel may have significant impacts on business operations. Many publicly traded U.S. companies actually discuss the potential failure to retain key talent as a risk factor in their 10-K filings. In this paper, I examine a firm's exposure to the risk of losing key labor inputs, and analyze its impacts on expected recovery rates and corporate bond spreads.

Firm-specific human capital is a valuable asset for generating future cash flows. However, those key assets may walk out of the door any day. In particular, there may be a large wave of voluntary or involuntary separations around default events, causing considerable losses to the firm's remaining asset value. For example, departures of key employees around the time of Lehman Brothers' failure made the company much less valuable than it used to be, as sales networks, trading skills, long-term customer relationships and other intangible assets were taken away by those leaving employees. Therefore, recognizing that Lehman Brothers is a labor-intensive company, financial investors understood ex-ante that there would be a sudden reduction in the firm's remaining asset value in the case of a default. Thus, investors should expect a low recovery rate and require a relatively high bond spread for compensation. In fact, Fleming and Sarkar (2014) show that creditors of the Lehman Brothers holding company (LBHI) only received 21.34% of their allowed claims in the aggregate, and argue that "even after accounting for possibly reduced recovery rates owing to adverse credit and macroeconomic conditions, the recovery rate so far for LBHI has been low compared with the historical average."

Recent literature has already studied the impact of labor market variables on asset prices. However, previous papers mainly look through the lens of default risk. For example, Eisfeldt and Papanikolaou (2013) argue that because of systematic fluctuations in the division of surplus between key employees and shareholders, investing in firms with high organization capital exposes shareholders to additional risks, and that firms with more organization capital are riskier and have higher average returns than firms with less organization capital. Donangelo, Gourio, Kehrig, and Palacios (2016) demonstrate that high labor-share firms have operating profits that are more sensitive to shocks, and higher expected asset returns, since labor-induced operating leverage amplifies firm risk in a way that is analogous to financial leverage.

In contrast, this paper focuses on impacts of the labor risk on bond spreads through an

expected recovery rate channel. Through the lens of default probability, a labor-intensive firm tends to have a higher operating leverage, a higher asset volatility, a higher default probability and a lower asset price than its counterpart, while through the recovery rate channel, the firm will have a lower expected asset value given default, a lower expected recovery rate and a lower asset price. In other words, through the recovery rate channel, the underlying asset value process is not continuous. As a result of the potential loss of human capital assets, investors expect a downside jump conditional on default, where the size of the jump depends on the proportion of human capital assets among total assets.

In addition, the recovery rate channel effects matter greatly for bond spreads, but less so for stock prices, while the default probability channel effects play an important role in both stock and bond markets. This is because the stock value upon default should be close to zero, and then variations in the remaining asset value are not going to be a major concern for equity investors.

Finally, firms can partially undo the default probability channel effect of the labor risk on asset prices, but there is less they can do for the effect through the recovery rate channel. Sun and Zhang (2017) and Favilukis, Lin, and Zhao (2017) find that rising labor-induced leverage shrinks the firm's debt capacity and financial leverage, mitigating the overall risk. On the other hand, because labor intensity is an equilibrium outcome ultimately determined by the firm's fundamental production technology, adjustment in labor intensity can be costly or even infeasible, and because investors should expect a low recovery rate given the high labor intensity, impacts of the labor risk through the recovery rate channel may not be mitigated. Endogenous responses such as reducing financial leverage only help with the default probability but not the loss given default. For all reasons above, the recovery rate channel should be at least as important as the default probability channel in understanding how the labor risk affects credit spreads.

Examining the recovery rate channel effect of the labor risk on bond spreads presents three key empirical challenges. First, disentangling the recovery rate channel effects from the default probability channel requires data availability on firm-level expected recovery rates. The most widely used measure is Moody's realized recovery rate data, computed from post-default trading prices. This data does not measure expected recovery rates that are more relevant for bond valuation, and it only covers a small set of companies which actually default, with potential selection bias problems. The second challenge is to show the empirical relevance of recovery rate variations for bond spreads. The prevailing practice in bond valuation is to assume a

"rule of thumb" recovery rate for all bonds, for example, 40%. The common argument is that recovery rate variations don't matter too much given small default probabilities. Finally, deriving a causal relationship of the labor risk on bond spreads requires a strategy to address the potential endogeneity of labor market variables with respect to economic outcomes such as the financial leverage.

To address the first challenge, I contribute a market-based, model-free measure of firm-level expected recovery rates that can be obtained at a relatively high frequency and have a relatively large coverage. I do this by analyzing the difference between "pseudo spread" proposed in Culp, Nozawa, and Veronesi (Forthcoming), and actual corporate bond spread. The basic intuition is to obtain a proxy for recovery rates by comparing stock and bond prices, because recovery rate variations are differentially less relevant for equity pricing than for bonds, as opposed to default probability variations, which affect both stocks and bonds. The pseudo spread essentially extracts default probability information from out-of-money put options on equity, and converts this information into a bond spread that is more comparable to the actual bond spread. To be specific, a pseudo spread is the spread of a zero coupon bond issued by a pseudo company that only purchases the original firm's equity as its asset. With no-arbitrage pricing, the market price of the pseudo bond can be obtained from treasury rates and put option prices on the original firm's equity. By construction, pseudo and actual spreads should present a small difference in default probabilities and in discount rates, but a significant difference in recovery rates. This is because any pure recovery rate variation should have little impact on the original firm's equity value, or the pseudo firm's asset value. As a result, it only negatively affects the actual bond spread while leaving the pseudo bond spread unchanged.

Using this proxy of firm-level expected recovery rates, I study the relative contribution of recovery rate variations on bond spreads. I show the opposite of conventional wisdom that there are considerable cross-sectional and time-series dispersions in recovery rates, that incorporating those dispersions explains a significant amount of bond spread variations, and that recovery rate variations are particularly important for bonds with small default probabilities. I run panel data regressions of the log of bond spreads on the log of default probabilities alone, on the log of recovery rates alone, and a combination of both. Adding recovery rates explains close to 5% more bond spread variations. Then I re-run the regressions for investment-grade and high-yield bonds separately and find a differentially high incremental explanatory power for high rating bonds. This is also aligned with the fact that investment-grade bonds have negligible default probabilities but relatively lower recovery rates than they should have, given a high correlation

between default probabilities and loss rates.

I reconcile all empirical findings above with labor-risk related recovery rates: A labor-intensive firm will have a relatively lower recovery rate than it would have without the labor risk, but its default probability may remain inconsequential as a result of endogenous financial leverage adjustments. Hence, the detrimental impacts of labor intensity can be better understood through the recovery rate channel, while low default probability, low financial leverage and low equity volatility may lead to an underestimation of the firm's risk. Particularly, investment-grade firms are in general better firms which tend to have larger amounts of knowledge capital created within the firm. Hence, taking recovery rate variations into account better captures the rising risk associated with labor inputs and explains more of the bond spread, with a stronger effect for investment-grade firms.

To empirically assess such a relationship, I start by computing correlations between labor intensity measures and expected recovery rates. Along the time series dimension, the median firm-level labor share displays a strong negative correlation with average expected recovery rates. Sorting firms by labor shares also yields an overall negative cross-sectional correlation. In panel data regressions, I find that an increase in the labor share is associated with a significant increase in the bond spread.

Finally, I show a causality of the labor risk on recovery rates and bond spreads through quasi-experiments. In order to deal with the endogeneity concern that the labor share is an equilibrium outcome, I make use of plausibly exogenous aggregate labor market shocks, or to be specific, variations in the labor market mobility. Even though the firm's exposure is determined jointly in equilibrium with other corporate decisions, changes in the differential impacts between labor-intensive firms and counterparts are determined by the exogenous labor market shock: holding all else equal, those two groups of firms will present a larger price difference with a higher mobility shock, since labor-intensive firms are hurt more by rising mobility. It is as if the exogenous mobility shock amplifies the existing dispersions in labor risk exposures.

I consider exogenous changes in mobility constraint associated with the enforceability of "Covenants Not to Compete" following state court rulings. An unanticipated increase in labor market mobility improves the outside option value for employees, making retention even harder. Investors should then expect larger losses upon default and lower recovery rates for all firms affected, though high labor share firms are more sensitive to the mobility shock and should suffer more. Through a Triple-Difference design, I identify a significantly larger effect on spreads for high labor share companies following quasi-experiments. I find that a one percent increase in

the labor share causes an approximately 0.4% increase in the recovery rate, and a 0.6 basis point drop in the bond spread.

In summary, my work emphasizes the importance of the expected recovery rate channel regarding the consequence of risk evolving from labor markets on bond prices. From the perspective of financial investors, investing in labor-intensive firms is risky since key employees may leave the company upon default, resulting in a sudden drop in the remaining asset value and a lower expected recovery rate. Hence, the risk inherent in this type of firm-specific human capital requires significant compensation in the form of high bond yields.

My paper belongs to a growing body of work that explores the role of labor risk in explaining asset prices. Eisfeldt and Papanikolaou (2013), Eiling (2013), Belo, Lin, and Bazdresch (2014), Donangelo (2014), Kuehn, Simutin, and Wang (2017) and Donangelo, Gourio, Kehrig, and Palacios (2016) empirically investigate how labor market variables, including organization capital ratio, industry-specific human capital, job finding rate, labor market mobility, labor market matching efficiency and labor share, affect the cross-section of stock returns. Favilukis, Lin, and Zhao (2017) study the effects on aggregate credit spreads. This paper complements the existing literature: the key difference is that I'm focusing on an expected recovery rate channel explanation other than the default probability channel.

Moreover, this paper is related to the literature that tries to understand credit spread puzzles. Collin-Dufresn, Goldstein, and Martin (2011) find that default risk has rather limited explanatory power on credit spreads movements. Giesecke, A.Longstaff, Schaefer, and Strebulaev (2011) show that over the long term, default losses can only account for half of the credit spreads, and Gilchrist and Zakrajek (2012) argue that the predictive power of credit spreads on future economic activities mainly comes from the excess bond premium, which is defined as the difference between credit spreads and expected default losses. A common feature of these papers is that they assume explicitly or implicitly a fixed recovery rate for all bonds and all periods. Instead of focusing on the risk premium channel, my paper emphasizes the importance of cross-sectional and time-series variations in recovery rates. Huang and Huang (2012)find that credit risk accounts for only a small fraction of the spreads for investment-grade bonds, while I argue that recovery rate variations are particularly crucial for these high rating bonds with small default probabilities. Chen (2010) points out that the countercyclical default losses that arise endogenously through firms' responses to macroeconomic conditions help to address the credit spread puzzle. Since I have constructed firm-level recovery rates, I also evaluate the empirical relevance of cross-sectional dispersions. Cremers, Driessen, and Maenhout (2008) and

Culp, Nozawa, and Veronesi (Forthcoming) document the link between out-of-the-money put options and credit spreads and emphasize the importance of idiosyncratic tail risks. Siriwardane (2016) considers the tail risk of market fragility caused by capital losses of the largest sellers. Schmidt (2016) studies asset pricing implications of the tail risk of household labor income following job changes. As a complement, I'm looking into the tail risk associated with potential separations of labor force from the firm's perspective, and the distinctive nature of this tail risk is that sudden reductions in the asset value given default has little impact on the equity valuation and therefore cannot be simply modeled with a standard jump-diffusion asset value process.

Finally, this paper is built on the empirical corporate finance literature that links labor market variables with corporate operations. Garmaise (2011) and Jeffers (2017) investigate how the enforceability of "Covenants Not to Compete" affects corporate investment decisions. In particular, Jeffers (2017) shows that stronger enforceability leads to a substantial decline in employee departures, especially in knowledge-intensive occupations, supporting their validity as labor market mobility shocks.

The rest of the paper is organized as follows: Section II develops the recovery rate proxy, Section III details the importance of recovery rate variations for bond spreads, Section IV explores correlations between the labor share and the recovery rate, Section V establishes the causality, and Section VI concludes. Details on data construction are in the Appendix.

2 Measuring the Firm-Level Recovery rate

2.1 A proxy for expected recovery rate

Disentangling the recovery rate channel effects from the default probability channel requires data availability on firm-level expected recovery rates. Compared to the indirect approach that studies the recovery rate channel effects by controlling default rates and discount rates, it is preferred to directly measure recovery rates and look at how it is affected by the labor risk. I develop a proxy for expected recovery rates that is constructed to capture uncorrelated variations in recovery rates. Using this proxy as a laboratory tool to estimate how the labor market affects bond spreads should generate a lower bound on the true effect, since part of the true effect may go through the correlated default component that affects spreads in the same direction.

The key intuition is built upon the fundamental payoff structures of bond and stock covenants. According to standard structural credit risk models such as Merton (1974) and Leland (1994), the equity value becomes zero at the time of default. In other models, the equity value hovers near zero. Hence, recovery rate variations matter greatly for bond spreads, but less so for stock prices, while default probability variations play an important role in both stock and bond prices. Consequently, we can potentially obtain a proxy for recovery rates by examining the difference between stock and bond market information. However, a direct comparison of prices or returns is not applicable, as literature on market segmentation starting from Collin-Dufresn, Goldstein, and Martin (2011) suggests that there may be different discount rates for stock and bond market cash flows. In order to have a comparable counterpart to the actual bond spread, I construct a "pseudo spread" as in Culp, Nozawa, and Veronesi (Forthcoming) from stock market prices. The pseudo spread essentially extracts default probability information from out-of-money put options on equity, and converts it into a bond spread.

To be concrete, a pseudo spread is the bond spread issued by a pseudo company that only purchases the original firm's equity as its asset. On the liability side, the pseudo firm finances the purchase by issuing equity and zero-coupon debt with face value K and maturity T. The asset value of this pseudo firm is equal to the equity value of the actual firm, which is observable. At maturity, bond holders of this pseudo firm receive the minimum between K (no default) or the assets of the pseudo firm A_T^{Pseudo} (default). Thus, the payoff to bond holders is $min(A_T^{Pseudo}, K) = K - max(K - A_T^{Pseudo}, 0)$, which equals the payoff of a risk-free debt K minus the payoff on a put option on the pseudo asset. By no-arbitrage pricing, the value of the pseudo bond at any time t before maturity is:

$$KZ(t,T) - Put(A^{Pseudo}, K, t, T) = KZ(t,T) - Put(E^{True}, K, t, T) \qquad (1)$$

Where $Z(t,T)$ is the price of a risk-free bond of the same maturity. Recognizing that the value of pseudo asset is equal to the true equity value, we can obtain the market price of pseudo bonds from the corresponding treasury rates and put option prices on the original stock.

It is interesting to compare the market price of pseudo and true bonds. The difference between any two corporate bond spreads can be decomposed into a difference in expected default probabilities, a difference in expected recovery rates, a difference in discount rates, and combinations of those differences. However, by construction, pseudo and actual spreads should present a small difference in default probabilities, a small difference in discount rates, but a

significant difference in expected recovery rates.

First of all, there is a high degree of similarity through the default channel. Take the simplest Merton model for example. In a Merton world, the difference in default probabilities comes from either asset volatility or financial leverage. Because the pseudo firm maintains a very simple balance sheet, computing the financial leverage is straightforward. In principle, if the options market is liquid enough, we can potentially get a financial leverage that is very close to the original by varying the face value of the debt, or the strike price of the option. On the other hand, Ito's lemma suggests that the asset volatility of the pseudo firm, or the equity volatility of the original firm, highly correlates with the original asset volatility. For all the reasons above, default probability variations should only contribute marginally to the difference between pseudo and true spreads. Any default probability variation that affects the true spread will at least partially pass through to the pseudo spread.

Secondly, discount rate variations contribute little to the spread difference. Both pseudo and true bonds are bond market instruments, and the pseudo bond can be constructed to have a very similar maturity as the original bond if the options market is liquid enough. There is no reason that marginal investors assign very different discount rates for those two streams of bond market cash flows. Therefore, we can guess that discount rate variations are not crucial for the difference between pseudo and true spreads. Any discount rate variation that affects the true spread should at least partially pass through to the pseudo spread.

Finally, recovery rate variations should play a key role in the spread difference. Consider any pure recovery rate variation that is uncorrelated with default rate or discount rate variations. This negatively affects the true bond spread. In contrast, it will have little impact on the pseudo spread. Again, the fundamental reason for this is that equity valuation is insensitive to pure recovery rate variations. For the pseudo firm, the asset value and the financial leverage will not be affected. Because of that, the default probability of the pseudo bond remains the same. As the pseudo company only holds a simple financial asset–that is, the original equity–then the recovery rate of the pseudo bond remains unchanged as well. Lastly, a pure recovery rate variation does not affect the pseudo firm's discount rate. Hence, recovery rate variations will have little impact on the pseudo spread.

In sum, the difference between pseudo and true spreads is mainly driven by recovery rate variations. It is possible to back out recovery rates from this spread difference. Specifically, the proposed proxy is:

$$logCS^{Pseudo} - logCS^{True} \tag{2}$$

With higher expected recovery rates, the true bond spreads decline, while the pseudo ones remain unchanged, resulting in rising spread differences. Thus, I expect a positive correlation between the proxy and the expected recovery rate.

2.2 Evaluating the proxy

The simple spread difference has one additional very nice economic interpretation: the ideal experiment to establish a causality between the labor risk and asset prices is to find a "twin firm" that is otherwise identical to the original firm except for labor intensity. The pair of pseudo and original firm can be viewed as a close approximation to the ideal case, with great similarity in general, and a key difference in labor intensity, since the pseudo firm does not have any firm-specific human capital at all. As a result, the spread difference can be viewed as an approximation to the "ceteris paribus" effect of labor intensity, intangible capital ratio, and any other key differences between the pseudo and the original firm. Taking the form of spread difference and then looking into how labor market variables affect this spread difference helps to establish the causality, since the pseudo and original firms are much more comparable than two arbitrary firms in the cross-section.

I take the form of log-difference instead of level-difference because of the following: first, the cash flow part of bond spreads is equal to the product of the expected default rate and the expected loss given default. A logarithm allows me to approximate the log of the spread with a summation of the log of the default probability, the log of the loss rate, and residuals. In addition, a logarithm empirically yields a stronger linearity. Third, a logarithm helps to reduce the noise of extreme observations. Hence, taking the form of the log difference facilitates linear regression analysis.

There may still be concerns about the potentially spurious correlation between the actual bond spread and the proposed recovery rate proxy, when the proxy contains the spread itself. However, the pseudo spread is at a similar level as the original, and presents considerable time-series and cross-sectional variations that highly correlate with variations in the actual spread. Consequently, variations in the spread difference cannot be driven by the actual spread itself.

Another concern is that this proxy does not reflect the absolute level of recovery rates. I show in the following section that it correlates strongly with commonly used realized recovery rate measures, so the relative comparison in the cross-section and in the time series seems plausible. In addition, for the purpose of this paper, it is not necessary to obtain the raw recovery rate. For the purpose of getting the impacts of labor risk on bond spreads, I will

focus on the product of the partial derivative of spreads on recovery rates, and the derivative of recovery rates on labor measures. It is easy to show that if the measurement error between the proxy and the raw recovery rate is uncorrelated with spreads or labor measures, then the targeted product will be equal to the product where I replace the raw recovery rates by the proxy in the derivative computations. However, in order to have some idea of the absolute level, I regress the annual average of Moody's realized recovery rates on the proxy, and then use the estimation results to convert a firm-level spread difference into a predicted recovery rate. I adopt a "generalized linear model" as proposed in Papke and Wooldridge (1996) to guarantee that the predicted value falls between zero and one. Since I estimate the absolute level from the time series, I check its validity in the cross-section. It turns out to generate more-or-less similar outcomes as realized recovery rates. However, this transformation brings out additional problems: in principle, expected recovery rates may not be equal to realized ones. In addition, mapping expected recovery rates with realized ones computed from small samples may introduce a selection bias into the proxy. Finally, this additional layer of transformation increases the measurement error in the proxy. Hence, for all the regression analysis below, I mainly rely on the original spread difference as a proxy for recovery rates.

Then it comes naturally the concern about the default-related components in the spread difference. First, pseudo and actual bonds do differ slightly in default probabilities, and this difference will show in the proposed proxy. This suggests that the measurement error may correlate with spreads or labor measures, leading to a biased estimate of the impact of labor risk on spreads. In addition, part of recovery rate variations should correlate with default rates. For example, a macro shock shifts the default and recovery rate simultaneously. In order to establish a distinctive recovery rate channel effect, I should focus on pure recovery rate variations only and exclude any default-related part from the proxy. Hence, the residual of the spread difference from controlling for all variables that possibly matter for default rates should be a theoretically preferred proxy. This yields a lower bound on the recovery rate channel effects since it excludes all default-related parts from recovery rates, which interact with the spreads and labor measures in the same direction. Despite all these advantages in the residual of the spread difference proxy, the spread difference itself presents a great economic intuition, is very simple to understand and construct, does not yield additional measurement errors as in the residual construction, and can be more informative on the raw recovery rate. Hence, for the summary statistics, I mainly look at the spread difference. For the formal regression results below, I'm controlling for all default variables anyway to ensure the effect is going through the

recovery rate channel so that there will be no essential difference on regression results by using the spread difference or the residual proxy.

There may also be concerns about the measurement error that comes from the property of option markets. It is well known that option prices can be very messy. It may mainly reflect market liquidity, and other types of noises, other than fundamentals. In addition, the no-arbitrage relationship between the put option and the bond may not always hold for every company. However, the option market noise may not necessarily bias the final estimate. As long as the resulting measurement error being uncorrelated with spreads or labor measures, I can obtain an unbiased final estimate. Even if the option market noises generates a correlated measurement error, it may not be a severe problem. This is because the purpose of this paper is to establish a lower bound on the recovery channel effect of labor risk on spreads, and then any downside bias on the final estimate is still acceptable. More importantly, the proposed proxy presents a great advantage: Since it is completely market-based and does not rely on realized default events at all, it is possible to track the same company over time. This suggests that I can, for the first time, construct a panel data of recovery rates and spreads. Then, with the help of firm and time fixed effects, I can potentially eliminate the impacts of many kinds of measurement errors.

The final concern is that the proposed proxy relies on the assumption that equity value being insensitive to recovery rate variations. For example, in cases of chapter-11 defaults, the equity value may be well above zero. Then, recovery rate variations may have non-negligible impacts on the stock. As result, the proxy may present a low correlation with the raw recovery rate and a correlated measurement error with spreads or labor measures. Actually, for the validity of the proxy, it is not necessary to assume recovery rate variations having zero, or small impacts on equity value. Instead, the key assumption should be recovery rate variations having much larger impacts on the bond than on the stock, which seems more plausible. Under this assumption, the recovery rate difference may still have a larger order of magnitude than the default difference and contribute the most to the spread difference. Adding default controls and fixed effects strengthens the validity of the proxy even further.

It is also worthy to emphasize that the proposed proxy is a firm-level measure instead of issue-level ones. For instance, it can not capture recovery rate variations associated with debt seniorities. However, it is a good starting point for studying issue-level recovery rate variations.

Several advantages arise from the comparison with prevailing firm-level recovery rate measures. First, the proxy is completely market-based and model-free. Second, it can be obtained at

a relatively high frequency and in a timely fashion. Third, it is a measure of expected recovery rates as opposed to realized ones. Forth, since it does not rely on realized default events, it can potentially cover a larger set of firms and avoids selection bias problems. Finally, it allows tracking the same company over time.

2.3 Validating the proxy

I validate the recovery rate proxy by comparisons with prevailing measures. At the aggregate level, I compare it with average realized recovery rates in Moody's database and Altman-Kuehne/NYU Salomon Center database, obtained from Ou, Chiu, and Metz (2012) and Altman and Kuehne (2012) respectively; At the firm level, I compare it with estimated recovery rates of the same reference company, obtained from Markit credit default swap database.

Figure 1 plots the time series of the annual average of Moody's and Altman measures against the proxy. Moody's data ranges from 1982 to 2012, while Altman data spans 1984 to 2011. The proxy only dates back to 1996, at which time single stock option prices become available. Moody's determines recovery rates using closing bid prices on defaulted bonds observed roughly 30 days after the default date. Altman measures recovery rates using closing bid prices as close to the default date as possible. Both are value weighted. In contrast, the proxy measures expected recovery rates and is equally weighted. Nevertheless, these time series display a very similar pattern. The proxy has a correlation of 0.69 with Moody's, and 0.75 with Altman.

Cross-sectional comparison also confirms the validity of the recovery rate proxy. Table 1 provides data on the cross-sectional distribution of average expected and realized recovery rates by rating class. In general, both expected and realized recovery rates decrease with worsening credit ratings, which is reasonable given that default rates monotonically increase with ratings. However, recovery rates for top-rated categories seem surprisingly low. Average expected recovery rates for Aaa/AAA and Aa/AA bonds are lower than the investment-grade average, which is close to the commonly used number of 40%.

I have also compared the whole distribution of expected recovery rates with estimated recovery rates obtained from Markit credit default swap database. Overall, these two measures of recovery rates are highly correlated. The annual average expected recovery rate has a 0.52 correlation with Markit estimates, a similar number as above, and the cross-sectional correlation between two measures is 0.35.

As a final examination, I plot the annual average of expected recovery rates against credit spreads in Figure 2. Not surprisingly, aggregate movements in the recovery rates negatively

correlate with spread variations, supporting its validity as a proxy.

In sum, the constructed expected recovery rate proxy correlates with prevailing measures. It is empirically confirmed that this spread difference is actually capturing cross-sectional and time-series recovery rate variations.

3 Expected Recovery Rate and Credit Spread

The second challenge is to show the empirical relevance of recovery rate variations for bond spreads. The prevailing practice in bond valuation is to assume a "rule of thumb" recovery rate for all bonds, for example, 40%. The common argument is that recovery rate variations don't matter too much given small default probabilities. Accordingly, the recovery rate channel effects of the labor risk on bond spreads should not be of the first order of importance.

I study the relative contribution of recovery rates on bond spreads with the help of the proposed proxy. I show the opposite of conventional wisdom that there are considerable cross-sectional and time-series dispersions in recovery rates, that incorporating those dispersions explains a significant amount of bond spread variations, and that recovery rate variations are particularly important for bonds with small default probabilities.

The common practice in bond valuation of ignoring recovery rate variations already seems questionable given the great amount of dispersion in the measure. In Figure 3, I plot the time series of cross-sectional quantiles of the recovery rate proxy and find a significant dispersion along either dimension. The median of log spread difference can be as low as -1.14 in the recent crisis, and as high as 1.09 in 2006. Such a large dispersion can be translated into a 47% difference in recovery rates. For the cross-sectional distribution, the difference between the top quantile and the bottom quantile can be as large as 2.47 in 1999, which can be converted into an absolute difference of 50%.

Next, in order to run a competition between default and recovery rates, I compare summary statistics of both measures in Table 2. I also report summary statistics for the investment-grade average and the high-yield average to evaluate the relative importance of recovery rate variations by rating class. Investment-grade bonds do have higher recovery rates and lower default probabilities than the high-yield category. However, default rates monotonically increase with a worsening rating class, remain very close to zero for all investment-grade bonds, and spike quickly afterwards. In contrast, Table 1 already shows a different pattern in recovery rates: they are not even monotonically decreasing. I compare the standard deviation of default probabilities

and recovery rates. Recognizing they are of different scales, I normalize the standard deviation by dividing the mean. It turns out recovery rates display a larger cross-sectional dispersion than default rates. This is more pronounced for investment-grade bonds: the standard deviation for recovery rates is almost three times the mean, while it is less than twice the mean for default rates. Given relatively larger dispersions in recovery rates and the misalignment of default and recovery rates along the cross-section, recovery rate variations may be an important determinant of credit spreads, particularly for investment-grade bonds that have small default probabilities.

To further investigate the empirical importance of recovery rates, I regress the bond spread on the recovery rate alone, on the default rate alone, and a combination of both. Specifically, the regression is as follows:

$$logCS_{i,t}^{True} = \alpha_i + \gamma_t + X_{i,t}\beta + \epsilon_{i,t} \tag{3}$$

I estimate the model by double-demeaning. Table 3 displays the regression results which shows that recovery rate variations are as important as default probabilities. The incremental R square from Column 4 to Column 5 reveals the additional contribution of taking recovery rate variations seriously. I find that it explains approximately 5% more bond spread variations. This is a significant improvement, given the original R square by using default probabilities alone. The overall R square is close to 50%, similar to the literature. In addition, the point estimates suggest that with one unit increase in the recovery rate proxy, the log of the bond spread should decrease by 0.708. Plugging in an average spread, this suggests a spread drop of 12 basis points. Converting the recovery rate proxy into the right scale, this implies that a one percent increase of the recovery rate will decrease the spread by approximately 1.6 basis points.

To better understand the credit spread puzzle, I run regressions for investment-grade and high-yield bonds separately and find that recovery rate variations are particularly relevant for high-rated bonds that have small default probabilities. Table 4 displays the regression results. For investment-grade bonds, default rates can only explain a small proportion of bond spread variations while the recovery rate contributes relatively more in the sense of absolute R^2 and R^2 incremental. Adding recovery rate variations can explain 7% more investment-grade bond variations. For low-rated bonds, default probability variations emerge as the key driver.

There may be concerns that Merton Distance-to-Default is not a very good proxy for the true expected default rate and therefore the regression analysis above over-estimates the contribution

of recovery rates. Particularly, previous literature suggests that the default probability should reflect rising risks associated with the labor leverage. However, the Merton implied default probability already looks quite similar to Moody's realized default rate. Given the low level and the small dispersion in realized default rates, unless expected default probabilities can differ significantly from them, a better measurement of default cannot explain much more of the spread. In addition, I have already included other variables that may account for default risk. For instance, rising labor risk should show up in the idiosyncratic equity return and volatility. Still, I observe a significant effect of adding recovery rate variations.

Another concern is that the spread difference may be capturing default probabilities instead of recovery rates. As a robustness check, I repeat the main regressions above by using stock returns and dividend yields as the dependent variable instead of bond spreads. I find that the spread difference does not contribute marginally to stock market variables, contradicting the hypothesis that it is actually a better measure of default rates.

4   Labor Share and Expected Recovery Rate: Correlation

In order to reconcile the empirical findings above, I consider an important source of recovery rate variations: labor risk. A labor-intensive firm will have a lower recovery rate than it would have without the labor risk, since potential separations of key employees upon default is a big threat to the asset value. However, its default probability may remain inconsequential. Facing higher labor induced leverage, firms will either voluntarily reduce the financial leverage to control overall risk, or involuntarily face a tighter borrowing constraint as the promised compensation to key employees can serve as a debt-overhang. Nevertheless, firms will react to the labor leverage so that the overall default probability looks negligible. Hence, the detrimental impacts of rising labor intensity can be better understood through the recovery rate channel, while low default probability, low financial leverage and low equity volatility may lead to an under-estimation on the firm's risk. Investment-grade firms are in general better firms and tend to have larger amounts of knowledge capital created within the firm. Thus, recovery rates and bond spreads should reflect the differentially high sensitivity to the labor risk. In sum, taking recovery rate variations into account better captures the rising risk associated with labor inputs and explains more of the bond spread.

To examine the theory of labor leverage implied credit risk, I start by discovering empirical

correlations between labor shares and recovery rates. I find that companies with higher labor shares have relatively lower recovery rates, lower financial leverage but comparable default probabilities.

First, the empirical exercise requires a measure of the labor risk. Previous literature measures risk evolving from labor markets by an aggregate shock and heterogeneous exposures to the shock. Examples of aggregate shocks include labor market mobility, labor market matching efficiency, frontier technology or market wages. It measures the risk of a given labor force separating from the firm. On the other hand, exposures to the shock demonstrate the sensitivity of a firm's value to the labor market shock. It measures the proportion of the firm's assets that are exposed to such risk. Examples include the labor share as in Donangelo, Gourio, Kehrig, and Palacios (2016), defined as the labor cost divided by value added, which measures the importance of all labor force, and, the ratio of organizational capital to physical capital as in Eisfeldt and Papanikolaou (2013), which measures the importance of key personnel. This paper mainly focuses on the firm's heterogeneous exposure to the shock and how it affects the cross-section of bond spreads. In addition, the portfolio average of labor shares highly correlates with that of organizational capital ratios. Empirical results in the following sections remain robust to both measures. Hence, I will only report results based on the labor share in the main text.

Figure 4 plots the time series of average recovery rate and median labor share. Since the recovery rate proxy only dates back to 1996, I use Moody's annual average realized recovery rates instead to obtain a longer series for comparison. Thanks to the high correlation between expected and realized recovery rates, adding an expected recovery rate proxy does not change the graph significantly. The figure displays a strongly negative correlation between annual average recovery rate and labor share.

Table 5 looks into the cross-section and reports the median statistics for portfolios sort on the firm's labor share. I sort all companies in the sample into quintiles by their annual labor shares and re-balance every year. Then I compute the median statistics within each quintile for labor share, credit spread, equity volatility, expected recovery rate, implied default probability, financial leverage, and asset intangibility as in Rampini and Viswanat (2013). I choose to report the median instead of the mean to avoid the composition effect of superstar firms that have a large number of employees.

Consistent with Sun and Zhang (2017) and Favilukis, Lin, and Zhao (2017), financial leverage decreases with labor share, supporting the endogenous response facing rising labor risk.

As a consequence, the third and fourth quintiles have lower spreads, volatilities and default rates. However, this does not necessarily suggest that firms with higher labor shares are safer. A significant drop in the recovery rate proxy implies the opposite: those firms should observe higher spreads, if leverages remain unchanged. Hence, it seems that the harmful impacts of the labor risk can only get backed out with the help of recovery rates, while default rates and equity volatilities co-move with financial leverages and therefore are not very informative on the labor risk. The fact that firms with high labor shares have lower spreads, smaller default rates, but relatively low recovery rates suggests that recovery rate variations potentially matter to a great extent for these seemingly safe firms.

To formally examine the correlation between labor share and recovery rate, I run a panel data regression of the expected recovery rate on labor share, default probability, and other measures relevant for default including financial leverage, and bond characteristics. Specifically, the regression is as follows:

$$logCS^{Pseudo} - logCS^{True} = \alpha_i + \gamma_t + X_{i,t}\beta + \epsilon_{i,t} \tag{4}$$

Using the recovery rate proxy as the dependent variable instead of analyzing the bond spread directly affords several benefits. First of all, it is focusing on a pure recovery channel effect, by looking at recovery rates directly and by controlling default measures. In addition, recovery rates can reveal more about the effect of rising labor risk than bond spreads, since they are less affected by the firm's endogenous responses.

I estimate the model by double-demeaning. Table 6 displays the regression results. Labor share has a significant detrimental impact on the recovery rate. According to the estimation, a one percent increase in the labor share will significantly decrease the expected recovery rate proxy by 0.022 unit, or 0.2% in the absolute scale. Combing with the regression result from Table 3 that a one unit increase in the recovery rate proxy shrinks the log bond spread by 0.708 units, and plugging in an average spread, I estimate a spread increase of 0.9 basis points.

5 Labor Share and Expected Recovery Rate: Causality

The biggest challenge to further establish the causality of the labor share on the recovery rate and the bond spread is the potential endogeneity of labor market variables with respect to economic outcomes, such as financial leverage. To address this problem, instead of using the

bond spread as the dependent variable, I continue relying on the recovery rate proxy, which can be viewed as an approximation of the "ceteris paribus" effect of major differences between pseudo and original firms, while one key difference comes from labor intensity. Taking the form of spread difference and then examining how labor market variables affect this spread difference helps to establish causality, since the pair of pseudo and original firms is much more comparable than an arbitrary pair of firms. In addition, this proxy is constructed to capture pure variations in recovery rates uncorrelated with default or discount rates, which helps to demonstrate a pure recovery rate channel effect.

To address the potential endogeneity of labor market variables, since randomly assigning labor intensity to firms is not possible, it is necessary to find a source of variation that is otherwise uncorrelated with typical corporate finance variables. I use plausibly exogenous aggregate labor market shocks, or to be specific, labor market mobility variations that come from changes in the mobility constraint.

When local labor markets become more mobile, employees will have more outside options, which makes retention more difficult. For any given labor share, an exogenous increase in the labor market mobility will make the firm riskier in the sense that it is more likely to default and it will suffer a bigger loss upon default. Particularly, high labor share firms should suffer more and observe a sharper increase in loss rates and bond spreads, as a larger part of their assets is exposed to risk. Even though the firm's exposure is determined jointly in equilibrium with other corporation choices, changes in the differential price impacts between labor-intensive firms and the counterpart is determined by the exogenous labor market shock: Holding all else equal, those two groups of firms will present a larger price difference with a higher mobility shock. It is as if the exogenous mobility shock amplifies the existing dispersions in the labor risk exposures.

Following an expanding literature, especially Jeffers (2017), I focus on a particular restriction on labor mobility, "Covenants Not to Compete"(CNCs). CNCs are contract provisions that preclude employees from moving to, or establishing, a competitor for a period of time after leaving their employer. I rely on the change in the state-level variation in the enforceability of these contracts following state court rulings to tackle the endogeneity concern.

CNCs enforceability provides a good laboratory tool with which to study labor market mobility. There are several empirical facts regarding the popularity and effectiveness of CNCs: First of all, a large number of U.S. workers have at some time signed a CNC, or are currently subject to one. Second, CNCs could even apply to workers whose employment contract gets

terminated, validating the recovery rate channel story. Third, CNCs are more common for more knowledge-intensive positions. Fourth, an increase in CNCs enforceability leads to a significant drop in realized departure rate. Finally, the big drop in realized departure rate is mainly driven by workers in knowledge-intensive occupations.

Based on these results, a change in the enforceability of CNCs will have a larger effect for labor-intensive firms which tend to have higher labor shares; Additionally, a larger number of employees in such firms are working in knowledge-intensive positions and have signed a CNC; Third, the effect of reducing outside options is particularly strong for those knowledge-intensive workers.

The enforceability of CNCs varies across states. Some states, such as California, do not allow CNCs at all. More importantly, according to Jeffers (2017), between 2008 and 2014, seven state Supreme Court rulings and one law modified the state level enforceability of CNCs. Court rulings provide a particularly useful empirical setting because courts are not subject to lobbying and other pressures. Therefore, a change in the state level enforceability of CNCs can be used as an exogenous variation.

I use a generalized Triple-Difference approach with CNCs enforcement changes as the treatment of interest. The specification is as follows, for company i whose headquarter locates in state s and year t:

$$y_{ist} = a + \beta_1(T_s * P_t * H_{it}) + \beta_2(H_{it}) + \beta_3(T_s * H_{it}) + \beta_4(P_t * H_{it}) + bX_{it} + c_i + d_{st} + e_{ist} \quad (5)$$

For dependent variable of interest y_{ist}, I'm using the annual average of firm level expected recovery rate proxy. The "Treated" variable T_s is equal to 1 for an eventual increase in enforceability, 0 for no change, and -1 for a decrease in enforceability. This assumes a symmetry in the treatment effect following mobility increase and decrease. However, decomposing the treatment does not yield a significant difference. The "Post" variable P_t is equal to 1 for post-2008 period and 0 otherwise, where state court rulings started to take place. The "High" variable H_{it} is equal to 1 for upper half firms sorted annually by labor share and 0 otherwise. The usage of labor share portfolio instead of labor share itself reduces idiosyncratic measurement errors. More importantly, it allows small changes in the firm-level labor share following mobility movements. Unless the resulting labor leverage adjustment completely changes the cross-sectional ranking orders, which seems implausible, it will not bias the estimated effect too much. The parameter of interest is β_1, which measures the differential impact of changing mobility constraint on high

labor share firms versus the counterpart.

In addition, X_{it} refers to a vector of variables that could potentially affect the default probability, for example, Merton distance to default. Admittedly, including those time-varying variables that may be affected by mobility constraint yields an inconsistent estimate in β_1. However, the purpose of this exercise is to establish a lower bound on the labor effect through the recovery channel. Since the labor effect through the default channel works in the same direction for bond spreads, this only generates a downward bias, which is acceptable given the research question. I also include company fixed effects and state-year fixed effects in the regressions to take care of unobserved firm-specific characteristics and local conditions, and cluster all errors at the state level. The inclusion of fixed effects absorbs all terms that only contain the "Treat" variable T_s or the "Post" variable P_t or both.

The main assumption underlying this approach is that, absent the CNCs enforcement changes, the average change in the difference between high and low labor share groups, would have been the same for the treated group (the set of firms that eventually experience a CNCs-induced local labor market mobility change), and the control group (the set of firms that do not observe such changes). To examine the assumption, Table 7 compares the portfolio average of a High-minus-Low labor share portfolio for treated and control groups. I look at the level right before the enforceability change, as well as a three-year trend. The treated and control groups do not present significant differences in pre-treatment levels or trends. Hence, it is plausible that differences between high and low labor share firms will follow a similar trend in the treatment and control group without CNCs enforcement changes.

I estimate the model by double-demeaning. Table 8 reports regression results from the Triple-Difference design. As expected, an increase in the enforceability of CNCs will decrease the labor mobility and increase the recovery rates. The differential effect between high and low share firms is significantly positive, which means that the recovery rate increases more for high labor-share firms following a reduction in labor market mobility. From the point estimates, a High-minus-Low labor share portfolio will have a 0.25 unit increase in the recovery rate following a mobility reduction, or 2.08% in the absolute level. Combining with estimation results from Table 3 and plugging in an average spread, I estimate a spread drop of 41 basis points. Thus, a one percent increase in the labor share causes a approximately 0.4% increase in the recovery rate and a 0.6 basis point drop in the bond spread.

6   Conclusion

Potential separation of employees upon default reduces the expected remaining value of the firm's asset. Therefore, investors should expect lower recovery rates and require higher bond spreads for labor-intensive firms. I construct a market-based proxy for firm-level recovery rates and show that recovery rate variations are an important determinant of bond spreads in addition to default probabilities. I find that firms with higher labor shares have lower average recovery rates and higher spreads through quasi-experiments. Empirical results support the importance of the recovery rate channel effects of the labor risk.

Several research questions remain: First, this paper mainly investigates the implication of dispersions in the exposure to the labor market shock on credit spreads. It is interesting to measure the labor market shock per se as in Kuehn, Simutin, and Wang (2017) and investigate how the joint dynamics of aggregate labor shocks and idiosyncratic risk exposures affect spread changes and bond returns. Second, this paper is silent on the discount rate channel effect of the labor risk. Schmidt (2016) considers the asset pricing implication of the labor risk from the household's perspective and argues that potential extreme labor income after job changes may alter the risk premium. Although the proposed recovery rate proxy is constructed to isolate the discount rate channel effects and therefore should not yield a significant estimation bias, it is interesting to decompose impacts of the labor risk into default, recovery and discount rate components and estimate the relative contribution of labor-related expected default losses and risk premiums on bond spreads. Third, these three channels present a strong feedback effect of the labor market on asset prices. It is interesting to consider the equilibrium interaction between labor and financial markets with endogenous financial and labor leverage choices, and investigate if the fundamental labor market shock can account for a larger proportion of business cycle variations than previous literature suggests. Finally, the predictive power of asset prices on future economic activities may improve when taking into account cross-sectional variations in addition to the average time series, since those variations may reflect idiosyncratic exposures to the aggregate shock and can help predict the shock itself.

Figure 1: Expected Recovery Rate Proxy(left axis) and Realized Recovery Rate(right axis) . This figure provides data on time-series distribution of annual average recovery rates. Moody's and Altman realized recovery rates are computed from post-default trading prices and value weighted. Expected recovery rate is computed from the difference between the log of the pseudo bond spread and the log of the true bond spread and is equally weighted.
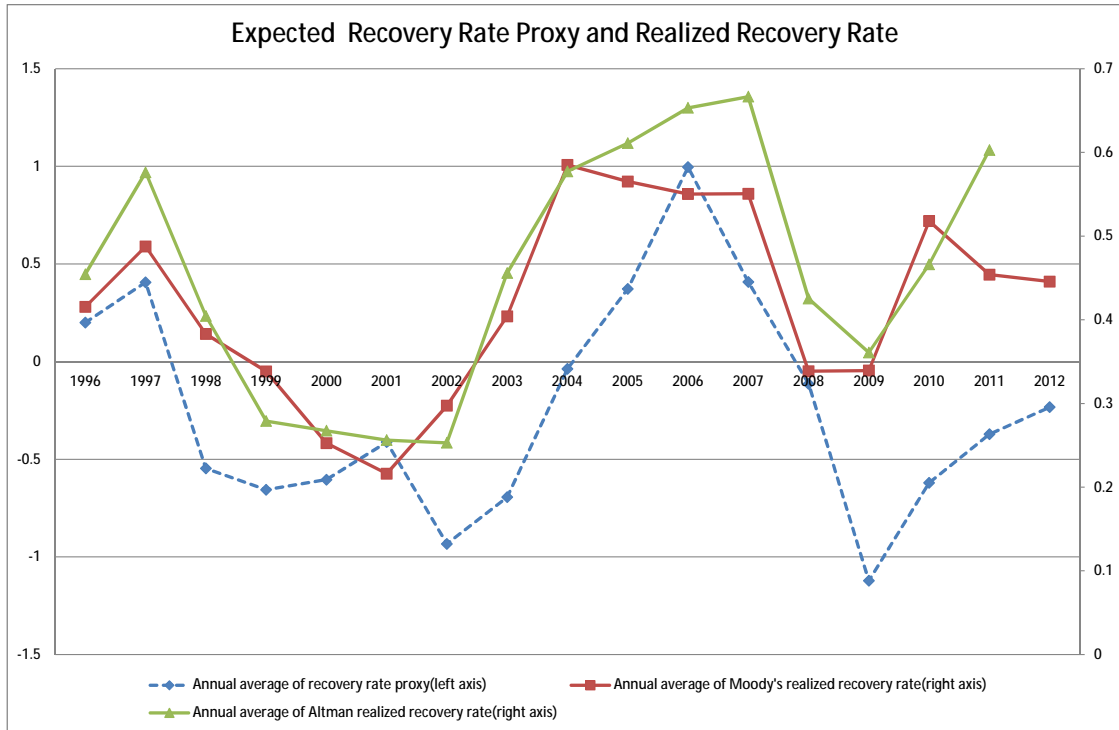
Figure 2: Expected Recovery Rate Proxy(left axis) and Credit Spread(right axis) . This figure provides data on time-series distribution of annual average recovery rates and bond spreads. Expected recovery rate is computed from the difference between the log of the pseudo bond spread and the log of the true bond spread and is equally weighted. Credit spread is computed as an equally-weighted average of corresponding option-adjusted spreads from the Lehman/Warga and Merrill Lynch databases.
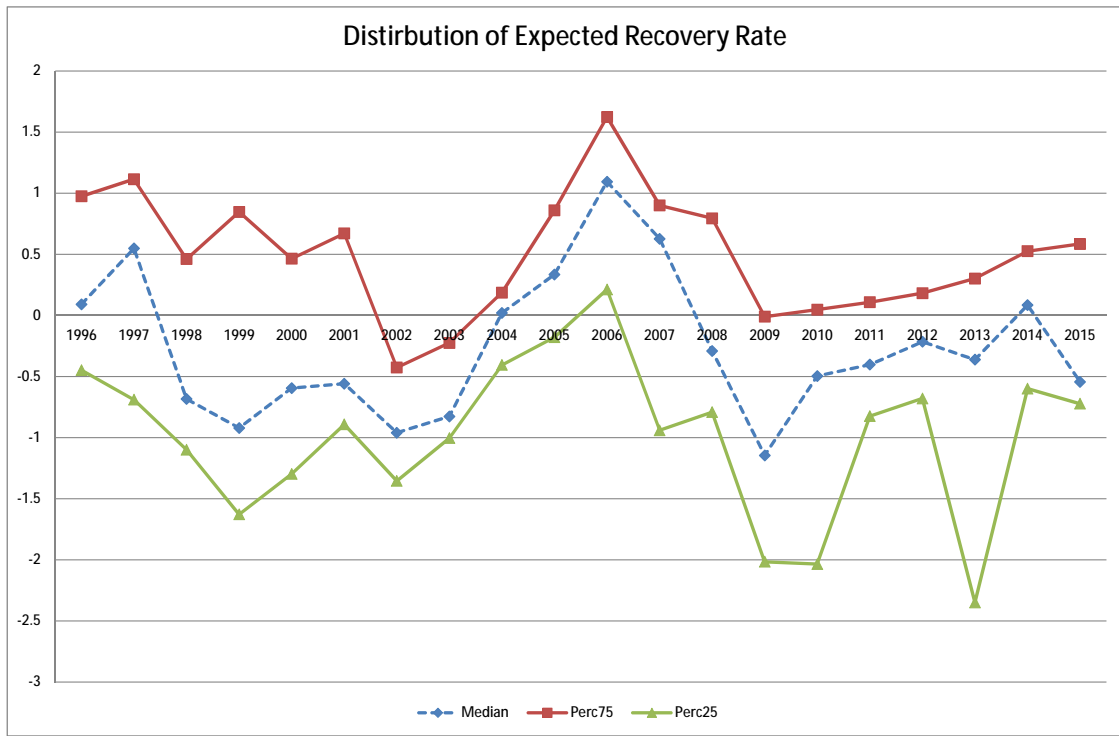
Figure 3: Distribution of Expected Recovery Rate. This figure provides data on the time-series distribution of 25, 50 and 75 percentiles of expected recovery rates. Expected recovery rate is computed from the difference between the log of the pseudo bond spread and the log of the true bond spread and is equally weighted.
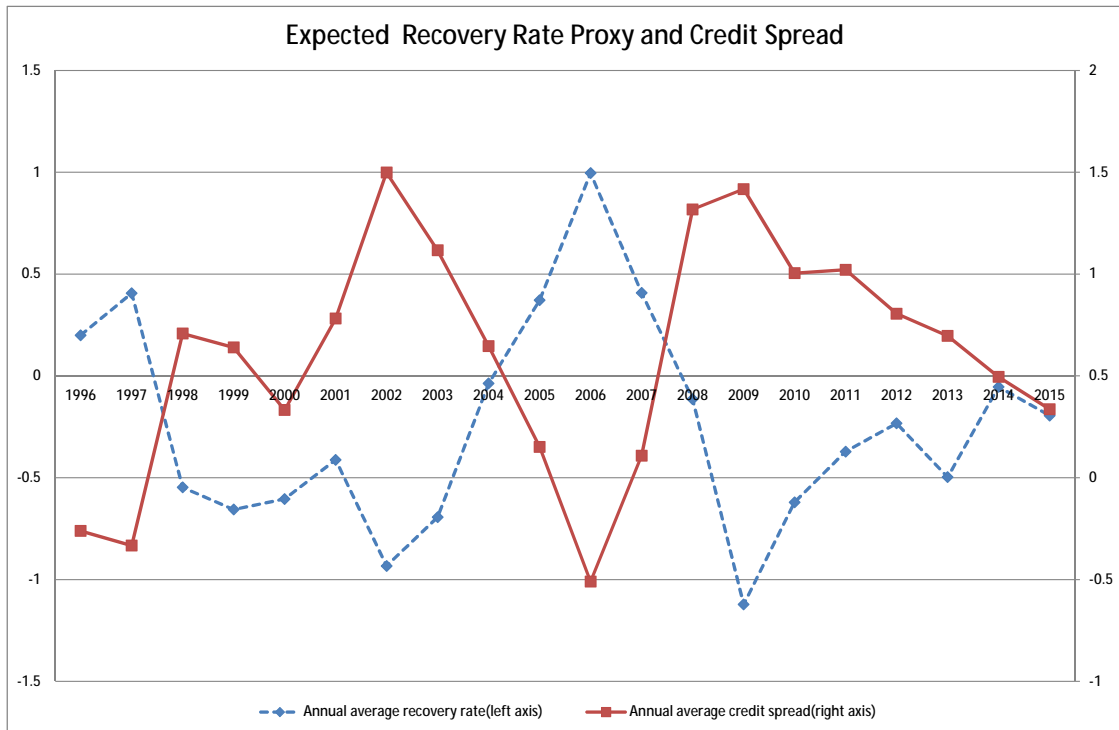
Figure 4: Realized Recovery Rate(left axis) and Labor Share(right axis). This figure provides data on time-series distribution of annual average realized recovery rate and median labor share. Moody's realized recovery rates is computed from post-default trading prices and value weighted. Labor share is computed as staff expense over value added.

Table 1: Expected Recovery Rate and Realized Recovery Rate. This table provides data on the cross-sectional distribution of recovery rates by Moody's or S&P rating. Column 1 provid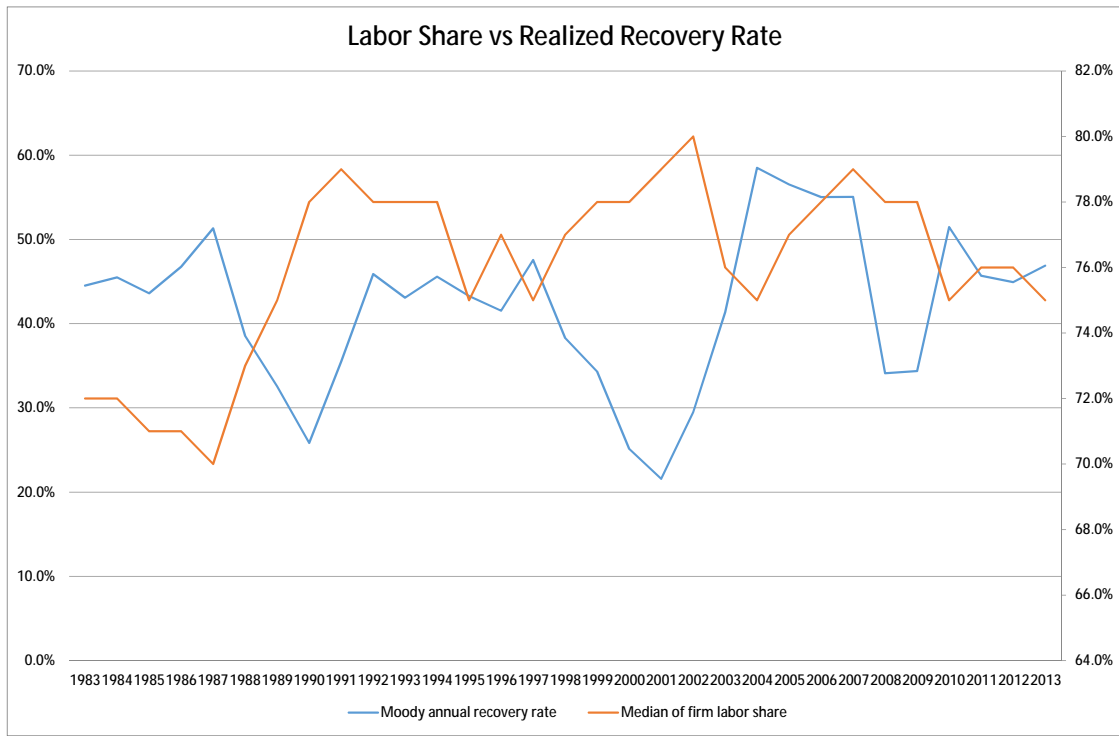es average expected recovery rates. It is computed from the difference between the log of the pseudo bond spread and the log of the true bond spread and is equally weighted. Column 2 converts the spread difference into absolute recovery rates with predicted values obtained from a time-series regression of realized recovery rates on expected ones. Column 3 to 4 presents Moody's and Altman value-weighted realized recovery rates computed from post-default trading prices.

Rating class	Expected Recovery Rate	Expected Recovery Rate Rescaled	Moody's Recovery Rate	Altman Recovery Rate
Aaa/AAA	-0.0187	0.3725	0.3603	0.8255
Aa/AA	0.0166	0.3966	0.4011	0.6039
A	0.2446	0.4255	0.4089	0.4717
Baa/BBB	0.1602	0.4010	0.4209	0.4007
Ba/BB	0.0084	0.3928	0.4427	0.3909
B	0.0017	0.3813	0.3772	0.3506
Caa-C/CCC	-0.0450	0.3614	0.3590	0.3728
IG	0.1697	0.4049	0.4181	NA
HY	0.0018	0.3814	0.3768	NA

Table 2: Expected Recovery Rate and Expected Default Probability. This table provides data on the cross-sectional distribution of recovery rates and default probabilities. Column 1 provides average expected recovery rates. It is computed from the difference between the log of the pseudo bond spread and the log of the true bond spread and is equally weighted. Column 3 presents average expected default rates computed from Merton Distance-to-Default model. Column 2 to 4 reports normalized standard deviations for recovery rates and default probabilities.

	Expected Recovery Rate Mean	Expected Recovery Rate Std/Mean	Expected's Default Rate Mean	Expected Default Rate Std/Mean
All	0.1055	1.42	0.0116	1.23
IG	0.1697	2.92	0.0015	1.86
HY	0.0018	0.91	0.0280	1.10

Table 3: Panel Data Regression of Bond Spreads on Expected Recovery Rates and Expected Default Probabilities. This table provides data on regression results of the bond spread on the recovery rate alone, on the default probability alone, and a combination of both. In Column 1, the set of explanatory variables $X_{i,t}$ only includes expected recovery rate. In Column 2, $X_{i,t}$ only includes Merton Distance-to-Default. Column 3 adds other measures relevant for default, including idiosyncratic equity volatility, stock return and financial leverage. Column 4 additionally considers bond-specific measures, including maturity, duration, coupon rate and age. Column 5 adds expected recovery rate to the set of the explanatory variables in Column 4. All variables are in the log form. Standard errors are reported in parentheses. *, **, and *** indicates significancy at 10%, 5% and 1% respectively.

$logCS^{True}$	(1)	(2)	(3)	(4)	(5)
$logCS^{Pseudo} - logCS^{True}$	−0.843***				−0.708***
	(0.040)				(0.038)
log(DD)		−0.019***	−0.005***	−0.014***	−0.014***
		(0.001)	(0.001)	(0.002)	(0.002)
Other default controls			Y	Y	Y
Bond characteristics				Y	Y
Time FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
R^2	0.205	0.236	0.261	0.386	0.430

Table 4: Panel Data Regression of Bond Spreads on Expected Recovery Rates and Expected Default Probabilities. This table provides data on regression results of the bond spread on the recovery rate alone, on the default probability alone, and a combination of both. Column 1 through 3 examines investment-grade bonds. In Column 1, the set of explanatory variables $X_{i,t}$ only includes expected recovery rate. In Column 2, $X_{i,t}$ includes Merton Distance-to-Default, other measures relevant for default probabilities, and bond-specific measures. Column 3 adds expected recovery rate to the set of the explanatory variables in Column 2. Column 4 to 6 looks at high-yield bonds and use the same independent variables as in Column 1, 2 and 3 respectively. All variables are in the log form. Standard errors are reported in parentheses. *, **, and *** indicates significance at 10%, 5% and 1% respectively.

| Rating | IG | IG | IG | HY | HY | HY |
$logCS^{True}$	(1)	(2)	(3)	(4)	(5)	(6)
$logCS^{Pseudo} - logCS^{True}$	-0.900^{***}		-0.755^{***}	-0.813^{***}		-0.579^{**}
	(0.038)		(0.035)	(0.038)		(0.195)
log(DD)		-0.012^{***}	-0.012^{***}		-0.016^{***}	-0.016^{***}
		(0.001)	(0.002)		(0.002)	(0.002)
Other default controls		Y	Y		Y	Y
Bond characteristics		Y	Y		Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
R^2	0.226	0.228	0.297	0.183	0.477	0.492

Table 5: Cross-Sectional Distribution of Labor share and Recovery rate. This table provides data on the median statistics for portfolios sorted on the firm's labor share. I sort all companies in the sample into quintiles by their annual labor shares and re-balance every year. Column 1 through 7 reports the portfolio median of labor share, credit spread, equity volatility, expected recovery rate, implied default probability, financial leverage, and asset intangibility respectively.

	LS	CS	Vol	Recovery	Default	Leverage	Tangibility
Low	0.35	2.49%	0.37	0.10	0.16%	0.63	0.75
2	0.50	2.53%	0.38	0.22	0.16%	0.59	0.60
3	0.65	1.58%	0.32	0.16	0.12%	0.47	0.43
4	0.75	1.75%	0.34	0.08	0.13%	0.48	0.42
High	0.86	4.94%	0.48	0.03	0.78%	0.55	0.35

Table 6: Panel Data Regression of Expected Recovery Rate on Labor Share. This table provides data on regression results of the recovery rate on the labor share alone, and a combination of the labor share and other variables. In Column 1, the set of explanatory variables $X_{i,t}$ only includes the labor share. In Column 2, $X_{i,t}$ includes Merton Distance-to-Default, other measures relevant for default probabilities, and bond-specific measures. Column 3 adds the labor share to the set of the explanatory variables in Column 2. All variables are in the log form. Standard errors are reported in parentheses. *, **, and *** indicates significancy at 10%, 5% and 1% respectively.

$logCS^{Pseudo} - logCS^{True}$	(1)	(2)	(3)
log(LS)	-0.011		-0.022***
	(0.018)		(0.006)
log(DD)		0.007***	0.005***
		(0.001)	(0.001)
Other default controls		Y	Y
Bond characteristics		Y	Y
Time FE	Y	Y	Y
Firm FE	Y	Y	YY
R^2	0.063	0.207	0.235

Table 7: Pre-Treatment Levels and Trends. This table provides data on pre-treatment levels and trends for the treated group and the control group. All variables are computed as equal-weighted portfolio average for the High-minus-Low labor share portfolio within each group. Row 1 through 5 reports the 2007 level of portfolio average labor share, credit spread, expected recovery rate, implied default probability and financial leverage. Row 6 through 10 reports the relative change from 2005 to 2007.

Variables	Treated Group	Control Group
LS_{2007}	0.35	0.33
CS_{2007}	1.50%	1.80%
$Recocery_{2007}$	-0.23	-0.17
$Default_{2007}$	0.52%	0.58%
$Leverage_{2007}$	-0.07	-0.09
$LS_{2007} - LS_{2005}$	0.06	0.04
$CS_{2007} - CS_{2005}$	0.36%	0.38%
$Recocery_{2007} - Recocery_{2005}$	0.08	0.03
$Default_{2007} - Default_{2005}$	0.09%	0.12%
$Leverage_{2007} - Leverage_{2005}$	0.01	0.01

Table 8: Triple-Difference Regression. This table provides data on Triple-Difference regression results. Column 1 provides the regression outcome without default controls. Column 2 provides regression outcome with default controls. All variables are in the log form. Standard errors are reported in parentheses. *, **, and *** indicates significancy at 10%, 5% and 1% respectively.

$logCS^{Pseudo} - logCS^{True}$	(1)	(2)
$Treat_s * Post_t * High_{it}$	0.326*	0.253**
	(0.185)	(0.122)
Default controls		Y
Firm FE	Y	Y
State-year FE	Y	Y
R square	0.156	0.283

A   Appendix

Corporate Bonds   I construct the panel data of corporate bond prices from the Lehman/Warga and Merrill Lynch databases. I obtain month-end secondary market option-adjusted credit spreads of outstanding senior unsecured bonds for the constituents of BAML index. I use similar restrictions as in Gilchrist and Zakrajek (2012) to ensure that the results are not driven by extreme observations.

Equity and accounting information   I match these corporate bonds with their issuers' annual income and balance sheet data from Compustat and daily data on equity valuations from Compustat database and the Center for Research in Security Prices (CRSP), which yields a matched sample of 2,355 firms for the period between January 1996 and December 2015.

Labor share is defined as in Donangelo, Gourio, Kehrig, and Palacios (2016):

$$\frac{XLR_{i,t}}{XLR_{i,t} + OIBDP_{i,t} + \triangle INVFG_{i,t}} \tag{6}$$

where XLR is the Compustat variable "Staff Expense-Total", OIBDP is the Compustat variable "Operating Income Before Depreciation", and $\triangle INVFG$ is the change in the Compustat variable "InventoriesFinished Goods". In case XLR is missing, I use the product of EMP, which is Compustat variable "Number of Employees", and the average annual labor compensation per employee in the industry during that year, to replace XLR.

Organization capital is defined as in Eisfeldt and Papanikolaou (2013):

$$O_{i,t} = (1 - \delta_O)O_{i,t-1} + \frac{SGA_{i,t}}{cpi_t} \tag{7}$$

where SGA is the Compustat variable "Selling, General and Administrative Expense". cpi denotes the consumer price index.

Financial leverage is defined as:

$$\frac{DLTT_{i,t} + DLC_{i,t}}{DLTT_{i,t} + DLC_{i,t} + CSHO_{i,t} * PRCC_{i,t}} \tag{8}$$

where DLTT and DLC are the Compustat variables "Long-Term Debt - Total" and "Debt in Current Liabilities - Total", CSHO is "Common Shares Outstanding", and PRCC is "Price Close - Annual".

Stock Options I use the OptionMetrics database for month-end prices on put options on individual stocks from 1996 through 2015 and apply the same filter as in Culp, Nozawa, and Veronesi (Forthcoming). I choose the strike price among contracts such that the implied leverage for the pseudo firm stays as close as the original firm as possible. I choose the maturity among contracts such that the remaining time to maturity stays as close as the original corporate bond as possible.

Treasury Rates I construct the risk-free zero-coupon bonds from 1-, 3-, and 6-month T-bill rates and 1-, 2-, and 3-year constant maturity Treasury yields obtained from the Federal Reserve Economic Data (FRED) database. I convert constant maturity yields into zero-coupon yields and linearly interpolate to match option maturities.

Credit Default Swaps I obtain month-end issue level estimated recovery rates for credit default swaps covering senior unsecured contracts from Markit database. I match it to the bond spreads of the same reference company.

Enforceability change of Covenants Not to Compete I obtain changes in the state-level enforceability of "Covenants Not to Compete" following state court rulings from Table 1 in Jeffers (2017).

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