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Does the productivity of labour influence credit risk? New evidence from South Korea

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Does the productivity of labor influence credit risk?

New Evidence from South Korea

Abstract

We find a positive relation between the productivity of labor in period t and credit ratings in period t+1, suggesting that firms that use the least amount of input (labor) to achieve output (sales) are considered to have decreasing levels of default risk. After we divide our sample into investment grade and non-investment grade firm samples, the relation changes. We find a consistent relation for the investment grade sample. However, the relation is negative for the non-investment grade suggesting that market participants capture NIG firm's potential detrimental behavior.

I. Introduction

We investigate the relation between labor productivity and credit risk. More specifically, we empirically test the relationship between the efficiency of labor in period t and a firm's credit rating in period t+1, and whether credit rating agencies are able to interpret the marginal effect of labor productivity on default risk. The role of credit rating agencies is to provide an indication of a firm's financial risk comparative to market peers. Credit ratings are determined by financial and non-financial information such as a firm's business profile, size, stability,

business risk, management quality and financial strength; corporate governance measures are based on questionnaire data and interviews with key personnel (Kraft, 2015). Regardless of the nature of business, efficiency is likely to lead to lower credit risk.

There is evidence that the estimation of firm performance obtained with financial data is not free from bias because of caveats associated with opportunistic behavior (Ali and Zhang, 2008; Jung et al., 2013; Alissa et al., 2013), the catering hypothesis (Jarrow and Xu, 2010; Becker and Milbourn, 2011; Bolton et al., 2012) and off balance sheet finance (Kraft, 2014), suggesting that credit rating agencies may not be able to capture a firm's true level of credit risk. However, Mali and Lim (2015) find no evidence of significant a relationship between opportunistic earnings management and an increase in credit ratings in South Korea, suggesting that firms that engage in earnings management in period t are unlikely to benefit in period t+1. They interpret that credit rating agencies are able to capture opportunistic earnings management. With this in mind, we examine whether credit rating agencies have the expertise to capture the marginal effect of labor productivity; thus, examining whether credit ratings agencies have the knowledge and ability to provide accurate levels of default risk.

Productivity of labor indicates how much sales revenue (output) each employee can generate (input). Higher productivity can be achieved by either 1) increasing output (sales) while remaining at the same level of resources (number of employees) or 2) downsizing the workforce while maintaining the same level of sales revenue. Thus, there are the two possible strategies to improve labor productivity, by increasing output or decreasing input. More efficient managers are likely to demonstrate superior operational performance, planning, leadership, adaptability and corporate governance, and are therefore able to keep wage

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expenses at the optimum level to achieve the highest level of labor productivity. Firms with higher levels of default risk are likely to be less efficient with weaker operational performance. Thus, they may only be able to increase labor productivity in the short-term by reducing employee levels. However, this action is likely to have a negative influence on the organization. Thus, we posit that after controlling for financial and non-financial determinants, credit rating agencies should be able to capture the marginal influence of labor productivity on default risk.

Using a sample of 1,666 KRX firm-year observations from 2002-2013, we find evidence that the productivity of labor in period t has a significant positive association with credit ratings in the subsequent period. We interpret that labor efficiency in period t is captured and therefore rewarded by credit rating agencies in period t+1. This interpretation is consistent with previous literature that suggests that credit rating agencies require a sufficient time frame and are generally slow to change credit ratings (Altman and Rijken, 2004; Hovakimian at al., 2009). Thus, overall, we find efficient labor productivity in period t has a positive influence on a credit rating agency's perception of default risk in period t+1.

Next, we further partition our entire sample into investment grade firms (IG hereafter) and non-investment grade (NIG hereafter) firms because IG firms and NIG firms are considered different with regards to corporate operations by banks, investors and other stakeholders. Overall, we conjecture that firms with lower productivity may be riskier; hence it is likely that there is a different relation for IG and NIG firms because of fundamentally different levels of operational performance, planning, leadership, adaptability and corporate governance. We partition our main sample into two groups, 1) safer group (investment grade firms) and 2) riskier group (non-investment grade firms) and the test the relation between the productivity of

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labor in period t and credit ratings in period t+1 is different for NIG and IG samples. We find conflicting results for IG and NIG firms. Specifically, we find a positive association between the productivity of labor and credit ratings for IG firms, consistent with our main sample. However, there is a statistically significantly negative association between labor productivity and credit ratings for NIG firms. We interpret that IG firms tend to be larger, and have superior organizational systems that enables them to obtain maximum production with the minimum input of labor. As a result, IG firms are more likely to increase output (sales revenue) with given resources (labor). On the other hand, NIG firms tend to be smaller, and are more likely to face financial distress, implying that management may not be in a position to raise sales, but in a position to downsize labor input and reduce labor expenses. Thus, a reduction in employees would temporarily increase sales to achieve short term gains at the cost of long term objectives. Thus, the short term gain achieved by a reduction in labor costs is likely to have a negative effect on the long term performance of the organization, and captured by credit rating agencies. This result is consistent with firms with lower credit ratings having weaker internal controls, corporate governance and monitoring (Bhojraj and Sengupta, 2003; Ashbaugh-Skaife et al., 2006).

To our knowledge, we are the very first to examine the relation between the productivity of labor and credit risk. Our results suggest that the productivity of labor influences a firm's credit rating levels. Moreover, we find that credit rating agencies are able to capture the marginal effect of labor productivity on credit ratings. Previous studies suggest that sales per capita, a major measure for corporate performance should be interpreted with caution because of the potential for managers to act opportunistically to influence earnings. We suggest that

labor productivity is a measure with additional explanatory power to explain firm performance, especially with regards to firm risk and the ability of firms to use resources efficiently. Taken together, these findings suggest that IG firms efficiently use resources to maximize profit, and this efficiency is captured by credit rating agencies whereas NIG firms are likely to achieve high productivity by reducing labor in period t because sales are more difficult to ascertain. We find that the reduction in labor is considered to have a negative influence in period t+1 and results in lower credit rating levels. Our results may be of interest to market participants who believe sales per capita is an important metric for financial performance and question whether the productivity of labor influences credit risk.

The remainder of the paper is organized as follows. Section II reviews previous literature and develops hypotheses. Section III includes our research design. In section IV, we analyze and interpret empirical results. In section V, we perform additional analysis. Finally, section VI concludes.

II. Previous literature and Hypothesis development

2.1 Literature review

A credit rating provides a systematic and independent appraisal of a firm's level of default risk. A firm's default risk indicates the possibility a firm will fail to make principal and interest payments under the bond's terms (Standard and Poor, 2012). A firm's credit rating provides bond holders, stakeholders, the general public and legislators with information about a firm's 'going concern' status. Firms with similar credit ratings are grouped together as firms of similar

credit quality (Kisgen, 2006). A firm's credit rating provides an 'economically meaningful role' by facilitating equilibrium in bond investment (Boot el al., 2006). A firm's credit rating is determined using financial data and supported by corporate governance data. A firm's financial data is evaluated using an ordinal grid that evaluates the strength of a firm's business profile, size and stability, business risk, management quality and financial strength (Kraft, 2015). Moreover, soft data is collected in the form of interviews with senior management (Parnes 2012); questionnaire data is collected to measure corporate governance risk using a similar ordinal quantitative scale. The ordinal scale is converted into a letter grouping to represent a firm's credit ratings. In South Korea, there are ten broad categories AAA, AA, A, BBB, BB, B, CCC, CC, C, D, with each category from A to D increasing in risk. The broad categories AA to CCC are further divided into 'notch' subcategories with +/-. A credit rating increase or decrease will occur if a credit rating agency collects enough evidence to suggest that changes in a firm's risk structure warrants a change relative to a firm's peers.

Management's primarily objective is to maximize the wealth of shareholders. Thus, *ceteris paribus*, management are likely to have long term plans to increase performance. Productivity growth within an organization can be accounted for by a constant reduction of less productive units and the reallocation of resources to more productive parts of the organization (Foster et al., 2001; 2005; 2006). Low productivity firms are less likely to survive and thrive compared to more efficient counterparts. Thus, the link between productivity and performance is not only required to increase shareholder wealth, but the relation between productivity growth and resource allocation is considered fundamental to a firm's survival (Ericson and Pakes, 1995; Melitz, 2003). Since the demise of Enron, WorldCom and the 2008 financial crisis, there has

been an increased interest in a firm's levels of default risk and creditworthiness. However, there is evidence that the financial ratios used to calculate firms' corporate performance are not true measures of corporate performance due to managerial opportunism, the catering hypothesis and off balance sheet finance. Thus, credit rating agencies may not be able to fully reflect the default risk of firms.

Dichiev et al. (2013) collect survey evidence that shows managers are deeply concerned about maintaining sustainable earnings. This concept is consistent with established literature that suggests that managers are likely to use discretionary accruals to smooth earnings to meet earnings targets to achieve benefits (Jones, 1991; Dechow and Dichiev, 2002; Kothari et al., 2005). However, a firm is unlikely to use accruals earnings management in isolation. Firms are likely to use a combination of real earnings management (Roychowdhury, 2006; Gunny, 2010; Cohen and Zarowin, 2010) and accruals earnings management because it is likely that using accruals earnings management to meet earrings targets is impossible at the end of the year if there is a revenue shortfall; moreover, accruals earnings management is more likely to be detected by auditors (Cohen and Zarowin, 2010). Graham and Harvey (2001) collect survey evidence from CFOs in the U.S. and Canada; they find that a firm's primary concerns when issuing debts are financial flexibility and credit ratings. Firms at plus or minus 'notches' are more likely to engage in earnings management to influence credit ratings (Ali and Zhang, 2008; Jung et al., 2013; Alissa et al., 2013).

Credit rating agencies are service providers and can only operate with funds from clients. Thus, credit rating agencies are likely to have a close relationship with clients for operational reasons. Moreover, potential clients are likely to shop for beneficial credit ratings to obtain the

lowest indication of default risk. This behavior is similar to clients 'opinion shopping' for favorable audit opinions. There is evidence that credit rating agencies cater to clients by providing higher credit ratings than a firm's credit risk warrants because of 'rating shopping' or shopping for favorable opinions due to sensitivity to debt covenants changes (Paradi et al., 2004; Jarrow and Xu, 2010; Becker and Milbourn, 2011; Bolton, 2012; Kraft, 2015). An additional factor likely to influence credit ratings is off balance sheet finance. A firm may acquire equity for legitimate reasons to increase productivity, or for opportunistic reasons to influence credit ratings. Kraft (2014) finds evidence that firms are likely to manage financial statements with off balance sheet debt. Moreover, there is evidence that firms manage leverage structures to achieve the highest future credit ratings relative to cost (Kisgen, 2009; Hovakimian, 2001; Hovakimian et al., 2009).

Therefore, there is an extensive literature that suggests managerial opportunism, catering and off-balance-sheet finance may lead to bias estimation of firm's credit ratings; moreover, the literature suggest credit rating agencies may not have the expertise or sophistication to capture a firm's true level of default risk because of the above caveats. However, whilst there is a potential for credit rating agencies not to have the ability to capture a firm's true level of default risk, Mali and Lim (2015) find that in a Korean context, firms that engage in earnings management in period t are less likely to experience credit ratings increases in future periods. Moreover, they find that firms with higher credit ratings are less likely to participate in earnings management, and find evidence consistent with credit ratings capturing the marginal influence of corporate governance and financial performance.

We posit that efficiency in terms of labor productivity is applicable in the context of credit

risk, and credit rating agencies are able to capture its effect on a firm's default risk levels. To our knowledge, we are the first to test the relation between credit risk and labor productivity. Changing the levels of employee levels through redundancy and recruitment is likely to have a significant influence on a firm's risk. Thus, labor productivity should be included by analysts when calculating credit ratings and corporate performance. It is established that sales per capita is a major metric for the productivity of labor since it indicates how much sales revenue (output) each employee can generate (input). Thus, a question arises whether high labor productivity in period t is an applicable measure for a firm's future performance in period t+1, and whether this phenomenon influences a credit rating agency's perception of risk. Higher productivity can be achieved by either 1) increasing output (sales) while remaining the same level of resources (number of employees) or 2) downsizing the workforce while maintaining the same level of sales revenue. The former suggests that a firm is indeed efficient since sales increases with the given resources (firm efficiency), whereas the latter may yield potential risk in subsequent periods. A firm is likely to have short, medium and long term plans dependent on products, goods and services with varying life cycles. We conjecture that experienced managers have superior knowledge, and are likely to give more accurate forecasts about salary expenditure compared to less experienced managers. A less experienced manager is likely to require a higher number of employees relative to sales; thus giving firms with higher labor productivity a comparative advantage in the market. Thus, we conjecture that labor productivity can be considered a parsimonious proxy for operational performance, planning, leadership, adaptability and corporate governance. Thus, superior organizations are more likely to keep wage expenses at the optimum level to achieve the highest level of labor productivity.

However, we predict that the relation between labor productivity and credit ratings will not be equal for IG and NIG firms. Investment grade (IG) firms have credit ratings from A- to AAA, whilst non-investment grade firms' (NIG) credit ratings are BBB+ and below. IG and NIG firms are considered to be different by investors, banks, and insurance brokers. There are several costs associated with NIG status. Changes in the credit structure of NIG firms can trigger debt covenants. Firms below the investment-grade threshold have limited access to investment; Rule 2a-7 of the Investment Company Act of 1940, stipulates limitations on investments in NIG firms. Moreover, NIG firms incur higher rates from suppliers and may have difficulty attracting investment. Thus, we hypothesize that IG firms have superior operational performance, and are therefore more likely to keep wage expenses at the optimum level to achieve the highest level of labor productivity. In periods of financial distress, NIG firms may be tempted to seize any opportunity to increase profit, hence downsize its number of employees in order to reduce expenditure. In this situation, firms may increase short-term profit, but a reduction in staff can damage long term objectives, since the loss of important human resources is likely permanent. Thus, we conjecture that the relation between credit ratings in period t+1 and labor productivity in period t will be different for IG and NIG firms.

2.2 Hypothesis Development

Figure 1 illustrates our proxies for the productivity of labor. The proxy for labor productivity is output over input, computed as sales (output) divided by number of employees

(input). We hypothesize that labor productivity in period t influences credit ratings in period t+1. We specifically select a t+1 period because credit rating agencies have a desire to keep credit ratings relatively consistent, and do not change a firm's credit rating without sufficient evidence (Becker and Milbourn, 2011). Ratings are updated only when agencies are confident that observed changes in a company's risk profile are likely to be permanent; this behavior is known as the prudent rating migration policy (Altman and Rijken, 2004; Hovakimian at al., 2009). Therefore, we conjecture that labor productivity is likely to influence credit ratings in period t+1.

Management with the ability to effectively implement long, medium and short term goals and product life cycles are more likely to be efficient in their allocation of current assets. Thus, it is likely that these firms will be the most efficient in allocating current assets per unit of sale. To our knowledge, we are the first to examine the relation between labor productivity and credit ratings in the subsequent period; however, to a large extent, the relation is plausible, and commonsensical. We predict that overall, firms with the ability to maximize labor output per capita of sales in period t can be considered as firms with lower levels of financial risk in the following calendar year. Thus, we predict a positive relation between the productivity of labor in period t and credit ratings in period t+1. In short, a positive relation suggests superior management is able to achieve sales with an efficient level of labor per unit produced. Thus, giving firms with maximum labor productivity a comparative advantage compared to its peer; hence lower risk in subsequent periods. Based on the arguments above, we state our hypotheses as follows.

H.1. Firms with higher labor productivity/efficiency have higher credit ratings.

Hypothesis 2 is bi-directional dependent on a credit rating agency's sophistication and ability to capture the opportunistic behavior of riskier firms that sacrifice long term objectives for short term gain. The operational performance, planning, leadership, adaptability and corporate governance of IG and NIG firms are likely to be different. As discussed in H.1., more experienced managers are likely to have the ability to keep salary expenditure at its optimum level or at least a more efficient level compared to less skilled managers. Firms with higher labor productivity are likely to have a comparative advantage. Therefore, in periods of distress, firms with experienced managers, IG firms are likely to have the ability to increase profit by increasing sales. However, riskier NIG firms may not be able to increase sales; thus, may only be able to achieve targets by decreasing the number of employees. A different relation between the productivity of labor in period t and credit ratings in period t+1 for IG and NIG firms suggests that credit rating agencies capture the opportunistic behavior of NIG firms. If the signs are consistent, credit rating agencies may not consider the productivity of labor as a measure with the potential to influence credit risk. Based on the arguments above, we state our second hypotheses as follows.

H.2. The relationship between labor productivity and credit ratings for IG firms is different to that of NIG firms.

III. Research Design

3.1 Variable definition

Credit risk

A firm's credit risk is calculated using an ordinal scale. A credit rating of AAA is represented by an ordinal value of 17. A firm with a credit rating of AA+ takes an ordinal value of 16 with credit ratings and ordinal levels descending by a value of one to represent all firms within our sample. Firms with a credit rating of CCC+ and below are represented by an ordinal value of 1. Productivity of labor is estimated as sales revenue divided by number of employees. As the numerator 'sales revenue' increases compared to the denominator 'number of employees', our proxy for labor productivity increases. However, decreases in the numerator 'sales revenue' and increase the denominator 'number of employees' will reduce the value of labor productivity proxy. The relation between credit ratings and number of employees captures the relation between credit risk and a firm's output efficiency. We examine whether a firm's productivity in period t, influences a firm's credit rating in period t+1. Overall, we expect a positive relation between a firm's productivity in period t and credit ratings in the next calendar year for IG firms because firms with higher levels of labor productivity will be considered as having a comparative advantage. However, as we discuss in H.2 this relation may be different for IG and NIG firms because of different operational characteristics.

Productivity of labor (Sales per capita)

Our main variable of interest, the productivity of labor is defined as sales per capita. We calculate sales per capita by dividing output (annualized net sales) by input (total full time equivalents). A firm's sales per capita is calculated as annualized net sales divided by full time equivalents. Specifically, annualized net sales indicate a firm's performance output with given resources, whilst total full time equivalents indicate a firm's existing labor resources. The calculation of full time equivalents involves a three-step procedure. First, we collect the number of full time employees from the annual report. Second, we convert half-time employees to full time equivalents by dividing the number of part-time employees by 2. Finally, we combine both measures to calculate full time equivalents. Since the majority of firms do not provide total working hours, we deem that 2 part-time staff members are the equivalent of 1 employee on a full time equivalent basis. The following equation shows the calculation of our variable of interest.

$$Productivity\ of\ labor = \frac{Output}{Input}$$

$$= \frac{ANS_t}{FTE_t}$$

Where,

ANS   : Annualized net sales at time t

FTE   : Full time equivalents at time t

<Insert Table 1 about here>

$$CR_{i,t+1} = \gamma_0 + \gamma_1 Productivity_{i,t} + \gamma_2 Size_{i,t} + \gamma_3 LiquidityRisk_{i,t} + \gamma_4 Profitability_{i,t} + \gamma_5 CashRisk_{i,t} +$$

$$\gamma_6 Lev_{i,t} + \gamma_7 AEM_{i,t} + \gamma_8 REM_{i,t} + \gamma_9 Loss_{i,t} + \gamma_{10} Big4_{i,t} + \gamma_{11} Foreign_{i,t} + ID + YD + \varepsilon_{i,t} \quad (1)$$

Where,

Dependent variable

$CR_{i,t+1}$: Credit ratings at time t+1

Variable of our interest

$Productivity$: Labor productivity (=Sales revenue / Number of full time equivalents)

Control variables

$Size$: Natural logarithm of total assets

$LiquidityRisk$: (Current assets– Current liabilities)/Total assets

$Profitability$: Firm performance measured by operating income/Total assets

$CashRisk$: Cash risk measured by cashflow from operation/Total liabilities

Lev : Debt ratio (=total liabilities/total owners' equity)

AEM : Absolute value of discretionary accruals suggested by Dechow et al. (1995)

REM : AbCFO*(-1) + AbProd + AbSGA*(-1) suggested by Roychowdhury (2006)

$Loss$: A dummy variable that takes 1 if a firm's net income at time t is negative, 0 otherwise

$Big4$: A dummy variable that takes 1 if a firm's auditor is Big4, 0 otherwise

$Foreign$: Foreign investors' shareholdings (%)

ID : Industry fixed effect

YD : Year fixed effect

Control variables

Our control variables are based on previous literature. We identity 5 variable categories known to influence credit ratings; 1) financial performance, 2) size, 3) business risk, 4) earnings management and 5) monitoring strength. We further divide our categories into determinants to

establish the best proxies for each category. For example, previous studies use various proxies to represent a firm's liquidity risk. To establish the most robust model with the highest possible explanatory power, we test the relation between our dependent variable, credit ratings in period t+1, and various proxies for liquidity risk such as current ratio, quick ratio and cash ratio using scatter plots and correlation coefficients. The tests find that current ratio is the best proxy to explain the relation between liquidity risk and our dependent variable. This approach is repeated for all potential independent variables. Panel A of Table 1 illustrates our model selection process. In the left column, we identify the key determinants of credit risk. In the right column, all variables considered are listed. We highlight the variables with the highest explanatory power with bold font.

Panel B defines the variables selected as proxies for determinants. Size, the natural logarithm of prior year total assets is expected to be positive because larger firms are likely to have more resources at their disposal to overcome crises. Liquidity risk, a firm's current ratio is calculated as a firm's current assets minus current liabilities divided by total assets. We expect a positive relation between current assets and credit ratings because firms with higher levels of current assets relative to their current liabilities are less likely to have problems in making principle payments. Moreover, cash risk, cashflow from operation divided by total liabilities is expected to be positive. Lev, a firm's debt ratio is expected to be negative. Loss, a dummy variable that takes a value of 1 if a firm's net income is negative is expected to show a minus sign (Frye and Jacobs, 2012). We use numerous proxies to establish management quality. ABMJ, the discretionary accruals earnings management measure suggested by Dechow et al. (1995)

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and the real earnings management metric suggested by Roychowdhury (2006) are expected to be negative because opportunistic earnings management is likely to be punished by credit rating agencies. Our real earnings management proxies are based on Roychowdhury's model (2006). We identify three levels of abnormal 'real activities'; abnormal levels of cash flow from operations (CFO), production costs (Prod) and discretionary expenses (SGA). Deviations from normal levels of real activities are considered to be real earnings management (the residual from one of the three estimation models; 1) for AbCFO – Abnormal level of CFO, 2) AbProd – Abnormal level of production cost, and 3) AbSGA – Abnormal level of SGA). Positive deviations would be interpreted as earnings management for production costs (Prod). A negative deviation would be interpreted as management making upward earnings management decisions based on cash flow from operations (CFO) and discretionary expenses (SGA). We multiply the abnormal SGA and abnormal CFO values by the value of -1 to facilitate a consistent (positive value) interpretation. To capture the total effect of REM activities, we combine the three individual measures to calculate one comprehensive metric for REM activities; AbCFO*(-1) + AbProd + AbSGA*(-1) as suggested by Roychowdhury (2006). We include both earnings management variables in our regression because there is evidence in the extant literature to suggest that earnings management can be used as a strategy to influence credit ratings (Jung et al. 2013; Alissa et al 2013). Big4, a dummy variable that takes the value of 1 to represent firms followed by Big4 auditors, 0 otherwise is expected to be positive because firms followed by Big4 accounting firm's are likely to have better accounting quality and a higher levels of financial statement assurance (Jang and Rho 2016). Finally, Fore, foreign ownership is expected to be positive because large foreign investors are likely to develop robust corporate governance and

monitoring measures (Bhojraj and Sengupta, 2003; Ashbaugh-Skaife, 2006; Han et al., 2013).

Variables are winsorized at the top and bottom 1% to control for the effect of outliers.

3.2 Sample

We access financial data for all firms that borrow equity in the form of public bonds on the

KRX stock exchange from the TS-20000 and the KISVALUE DataGuide databases. Our sample

consists of KRX listed firms from 2002-2013. The initial sample consists of 2,080 observations.

Because our analysis establishes the relation of labor productivity and credit ratings on a t+1

basis, we delete an additional 362 firms, leaving a potential sample of 1,718. We exclude a

further 62 observations because of the unavailability of financial data, leaving a sample of 1,666

observations. Table 2 Panel A gives details of the sample selection process. Panel B provides

details about the distribution of our sample by credit ratings. Overall, we find that credit ratings

are normally distributed; the vast majority of credit ratings are on either side of the investment

grade threshold, the A and BBB broad categories.

<Insert Table 2 about here>

IV. Empirical results

4.1 Descriptive statistics

Table 3 Panel A gives the results of the mean (median) levels of our sample and mean (median) difference tests comparing our IG and NIG samples. We find that the labor productivity of IG firms is statistically significantly higher than NIG firms at 1% significance level (8.02), as are the results of all control variables. We find that IG firms are larger (19.62), more profitable (16.69), have higher levels of liquidity (4.21) and cash levels (8.83); have lower levels of leverage (-11.17), accruals earnings management and real earnings management. Moreover, IG firms are less likely to be loss making firms (-10.96) and more likely to be followed by Big4 auditors (11.22). Overall, the descriptive statistics demonstrate that IG firms and NIG are fundamentally different in all aspects that influence a credit rating agency's perception of risk.

Panel B gives the results of Pearson correlations, our dependent variable CR_t+1 is statistically significantly correlated with all independent variables at the 1% significance level. These relations are expected due to the fact we performed a series of robustness tests to develop the model with the highest explanatory power. Our independent variable of interest, the productivity of labor in period t has a positive correlation with credit ratings in period t+1, suggesting that labor productivity is increasing with credit ratings. All other control variables show the predicted signs. Since the coefficients are relatively low, and the VIFs of independent variables for all of our models are far below the threshold of 10, our results can be considered free from multi-collinearity.

<Insert Table 3 about here>

4.2 Multi-variate results

Table 4 illustrates the results of our main analysis. In column 1, we give details of our full sample, the combination of investment and non-investment grade firms. We find a positive relation between our dependent variable, credit ratings in the subsequent period and productivity of labor in period (Coefficient: 0.06, t value: 5.93), consistent with H.1. The results suggest that firms with higher productivity in period t are likely to have higher credit rating. We interpret these results as firms with efficient organizational systems, operational performance, planning, leadership and adaptability obtaining output with the most efficient amount of input compared to peer firms. The results show firms with higher labor productivity/efficiency achieve higher credit ratings. Moreover, firms with lower credit ratings are considered to be less efficient and unable to achieve the same level of sales output per employee. Thus, it is likely that credit ratings consider high labor productivity to be a comparative advantage. All our independent variables are statistically significant due to our battery of tests to establish the model with the highest possible explanatory power.

Next, we divide our sample into IG firms and NIG firms. When we divide our sample into IG and NIG firms, we find different results. We find a consistent positive relation between the productivity of labor in period t and credit ratings in period t+1 for the 915 IG firms (Coefficient: 0.06, t value: 5.22). However, the relation between labor productivity in period t and credit ratings in period t+1 is significantly negative (Coefficient: -0.07, t value: -5.47) for the 751 NIG firm sample. We interpret these results as IG firms having superior operational experience

compared to NIG firms. IG firms are likely to have the organizational expertise to maximize the use of current assets. Hence, IG firms are more likely able to manage product lifecycles and manage services to maximize output. On the other hand, NIG firms are likely less able to increase sales. To maximize profit, these firms are more likely to decree se employee levels. Therefore, whilst NIG firms are likely to demonstrate efficiency with sales per capita, this relation can be considered a sign of distress by credit rating agencies. All things being equal, firms of a similar size within a similar industry are likely to utilize a similar number of employees; thus, the number of employees per sales output is likely to remain stable in normal business periods. However, this relation is likely to reverse in relation to risk in periods of distress. We interpret that credit rating agencies have the ability to capture opportunistic firms with riskier business strategies that sacrifice long term objectives for short term gain (the reduction of input/employees for a short term profit increase).

<Insert Table 4 about here>

V. Additional analysis

5.1 Investment grade vs Non-investment grade firms

In our main analysis, we partition our sample into safer (IG) and riskier (NIG) samples to test whether different relations are observed for different groups. For robustness, we conduct additional tests using the entire sample to examine whether the relation between productivity of labor and credit risk in the subsequent period is different for investment and non-investment

grade firms using a dummy variable approach. A dummy variable takes the value of 1 for IG firms, 0 for NIG firms. We report our results in Table 5. Consistent with the main findings, productivity of labor is positively associated with credit ratings, suggesting that overall relation between labor productivity and credit risk is positive. However, when we interact the IG dummy with our main variable of interest (*Productivity*IG*), we find a significant positive association (Coefficient: 0.03, t value: 6.74), suggesting that the positive influence of productivity of labor on credit rating is stronger for IG firms compared to NIG firms. Consistent with our main results, we interpret that IG firms more efficiently use resources to maximize profit, and this efficiency is captured by credit ratings agencies.

<Insert Table 5 about here>

5.2 Different proxies for productivity of labor

In order to test our hypotheses, we use sales per capita (sales/number of employees) as a proxy for financial performance to calculate the productivity of labor. However, this proxy does not incorporate all expenses a firm may incur, hence the additional effects of all company expenses. To add robustness, we consider an additional financial performance measure to estimate the efficiency of labor productivity. We replace sales per capita for profit per capita defined as net profit divided by number of employees (full time equivalents) and repeat the analysis. Untabulated results suggest consistent results, suggesting that the productivity of labor has a positive/negative association with IG/NIG samples in period t+1.

5.3 Additional analysis by industry

Our study examines the relation between the productivity of labor in period t and credit risk in period t+1 after controlling for the key determinants of credit risk established in previous studies (business profile, size and stability, business risk, management quality and financial strength; corporate governance measures) additionally, we include year and industry effect variables. Klette and Griliches (1996) and Mairesse and Jaumandreu (2005) suggest that industry price fluctuations can affect production functions and productivity estimates. Thus, before conducting our main analysis, we partition our sample into 21 industries based on the Korean Industrial Standards and test whether different industries have a different relation between labor productivity and credit ratings in the subsequent period. Table 6 illustrates our additional analysis by industry. For brevity, we only show the coefficients with t values for the productivity of labor. Our results suggest that labor productivity tends to have a positive influence on credit ratings for headcount-intensive industries such as wholesale business and the food and beverage industry whereas a negative association is observed for capital-intensive industries such as transportation, biomedical and the electricity (energy) industry.

Furthermore, we repeat the analyses after partitioning each industry sample into IG and NIG firms. For brevity, we report untabulated results. Overall, we fail to find consistent results. Specifically, we find consistent using the wholesale industry (IG t value, 3.91***, NIG t value -2.72***), non-metallic minerals (IG t value, 2.03**, NIG t value -1.92*), and construction (IG t value, 2.54**, NIG t value -1.70*). However, in other industries, the results are overall

insignificant. We infer that inconsistent results are likely caused by insufficient sample size size because we first partition our sample into 21 industries, and we further divide each industry into two different groups; 1) IG firms, 2) NIG firms. Therefore, some industries have insufficient observations to conduct an industry specific analysis.

<Insert Table 6 about here>

5.4 Additional evidence of NIG firms and labor productivity

Although we find a significant negative relationship between lagged labor productivity and credit ratings in our main analysis, our arguments may be considered a conjecture rather than a finding. Therefore, we conduct several additional analyses to provide evidence that NIG firms actually achieve higher labor productivity by downsizing. First, we include the levels of employment as a direct control variable in our regression and examine whether the negative relation remains unchanged. Second, we also provide descriptive statistics to better understand if NIG firms raise labor productivity with smaller employment levels. Specifically, we include 1) correlations between labor productivity and numbers of employment for NIG firms, and 2) the relation between total sales and labor size (IG vs NIG firms).

For brevity, we report untabulated results. First, we find consistent results after controlling for the number of employees. The coefficients of productivity for 1) full sample, 2) IG sample, 3) NIG sample are 0.06*** (t value 2.15), 0.05*** (t value 4.04), -0.0 2(t value -6.29) respectively. Second, we find a positive correlation between sales and number of employees for both IG and NIG groups, suggesting that regardless of whether a firm is an IG or NIG firm, a firm

with more employees achieves higher sales. Third, we find a negative relationship between labor productivity and number of employees for the NIG group, however, an insignificant relationship between these two dimensions for the IG group. We interpret that NIG firms downsize labor (input) which in turn, increases productivity.

5.5 Consideration of business cycle

It is possible that the key finding of our paper is due to business cycles. During a time of recession, most firms tend to downsize their labor force; firms may also receive lower credit ratings in this period. When the economy recovers, most firms naturally encounter higher levels of sales and are likely to receive better credit ratings. Therefore, we conduct additional analyses to examine whether our results remain consistent after controlling for this periodic effect. Specifically, we collect the yearly economy growth rate (GDP growth rate) during the sample period and conduct three additional tests for robustness using the GDP growth rate. For brevity, we report untabulated results. First, we include a time-varying macroeconomic variable (GDP growth rate) as an economy growth control variable in our regression. We consistently find a positive relation between the productivity of labor and credit risk using the full sample (Productivity coefficient, 0.05, t value 5.73), the IG sample (coefficient 0.05, t value 5.10), and find a negative relation using the NIG sample (coefficient -0.06, t value-5.53) after controlling for the economy growth effect.

Second, we use a dummy variable to proxy for economy 'specification'. We interact the dummy with labor productivity to explain credit rating at time t+1, our dependent variable.

Specifically, we set the recession dummy as 1 if the GDP growth rate for each year is less than the average GDP growth rate during the sample period, 0 otherwise. For robustness, we replace average GDP with median GDP, but the results qualitatively remain unchanged. We continue to find a consistent positive/negative relation for the Full and IG/NIG sample after including the 'specification' dummy variable. Furthermore, the interaction term (Recession*Producitvity) for the NIG group shows a significant negative coefficient (-0.00, t value -1.93). We interpret that during a recession period, NIG firms tend to downsize their labor force to increase labor productivity which is compounded into credit ratings in the subsequent period.

Third, we partition our sample period into two specific periods; expansion and recession to examine whether the asymmetric effect from lagged labor productivity on credit ratings is still observed in both time periods. Table 7 shows the results of our robust series of tests after partitioning our sample into expansion and recession periods. Regardless of whether it is an expansion or recession period, we consistently find that labor productivity has a positive/negative relation with credit ratings at time t+1 for IG/NIG firms.

<Insert Table 7 about here>

5.4 Firm fixed effect

Productivity of labor, defined as sales per capita may have limitations in certain situations. Since our measurement entirely relies on the number of employees, rather than the cost of employees, a firm with a small number of highly paid employees might earn less profit compared to a similar firm with a high number of lower paid employees. Likewise, if a firm imposes more overtime on a large number of employees or acquires outsourced shift work by

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contractors, the results may yield the potential bias. Furthermore, our measurement may not provide useful information for capital intensive firms. In order to control for firms with unique features, we repeat the analysis after including firm fixed effect so that firms with individual features are controlled. Untabulated results suggest consistent results with the main findings. Specifically, productivity of labor has a positive association with credit risk at a 5% significance level (t value of 2.21) for the entire sample. Moreover, we find significant positive/negative associations for IG/NIG group with significance levels of 5% (t value 2.69) and 10% (t value - 1.84) respectively.

5.5 Sensitivity analysis (Different definition of investment grade)

Whilst credit rating agencies, banks, and insurance brokers consider IG and NIG firms differently, investors are likely to have a varying assessments of risk based on risk-taking, averse and neutral status. Investors are profit maximizing and may be willing to invest in a firm with a credit rating of BBB+ instead of A- because of a potentially lucrative return on investment. NIG firms must provide higher returns on investment if an investor is to bear additional risk. Our main analysis defines NIG firms with credit rating of 1 (<B-) to 10 (BBB+) and IG firms are ranked with an ordinal value of between 11(A-) and 17(AAA). For robustness, we conduct a sensitivity analysis by increasing the IG threshold to include firms just above/below the investment grade status. Table 8 shows the results of our sensitivity analysis. For brevity, we only list the coefficient and significance levels for our main variable of interest. We list the results of 7 separate models. IG firms are shown in Panel A, NIG firms are shown in Panel B. For example, IG12 in Panel A shows IG firms with a credit rating of A or above. Similarly, the results in Panel B

list the results of NIG firms with a credit rating of A- and below. In Panel A, the heading IG10

lists IG firms with a modified IG status of BBB+ and above, *etc*. Our results consistently suggest

that overall productivity of labor is significantly positively/negatively associated with credit

ratings for IG/NIG group, consistent with our main findings.

<Insert Table 8 about here>

5.6 Fama-Macbeth (1973) yearly regression analysis

There is a possibility that our results are affected by potential time series dependence in

the error terms because we run our empirical analysis using a pooled data. Moreover, our

results may not be consistent over our sample period. To address the issue of time series

dependence, we perform a procedure suggested by Fama and MacBeth (1973). First, we cross-

sectionally estimate our productivity of labor model as per our main analysis for each year in

the dataset. Second, we examine the significance of coefficients using the Fama and MacBeth

approach (1973). We find consistent results with our main analysis, and our battery of tests.

Untabulated results suggest that the productivity of labor coefficient is 0.13 for full sample,

0.10 for IG sample, and -0.03 for NIG sample. The results are significant at 1% level, suggesting

a significant consistent positive/negative relation between the productivity of labor and default

risk over time for IG group/NIG group.

5.7 Test for predictive validity

Before we specify our control variables, we consider key determinants that are likely to influence credit ratings. Then, to determine the robustness of our model, we perform the cross validation technique to test our model's predictive validity. First, we randomly divide our entire sample into two sets of data; training (60%) and holdout (40%) samples. Second, we conduct a stepwise regression analysis using the training sample, and only include variables with at-value of greater than 2.00. This process is repeated for every analysis to determine the best model (the model used in our main analysis). Next, we test the newly specified model from the training sample, against the holdout sample. Finally, we conduct a leave-one-out cross validation analysis to test the predictive validity of our model.

Untabulated results are consistent with our main analysis. The coefficients t-vales for the productivity of labor in our 3 holdout samples;1) full sample, 2) investment grade, and 3) non-investment grade, are 0.06 (5.05), 0.06 (4.41), and -0.03(-3.30). Moreover, the root mean square residual (RMR) and the mean absolute percentage error (MAPE) of the holdout sample are slightly higher than the training sample (less than 0.28), suggesting that the models have reasonably high predictive power. Therefore, we find evidence that all additional analyses are consistent with our main findings.

VI. Conclusion

Previous literature implies that it is possible that credit rating agencies may not have the ability to issue accurate credit ratings because of potential managerial opportunism, the catering hypothesis and a firm's ability to take advantage of off-balance sheet finance. The

ability of credit rating agencies to provide an accurate level of a firm's default risk relative to peer firms has increased significantly since the recent financial crisis and the demise of Enron, WorldCom amongst others. Therefore, we examine whether Korean credit rating agencies have the expertise to capture the influence of labor productivity/efficiency on firm risk. To examine the sophistication of credit rating agencies, we examine whether credit rating agencies have the ability to capture the marginal influence of labor productivity in period t on credit ratings in period t+1. We use a t+1 approach specifically due to the prudent rating migration policy that suggests that rating agencies are slow to change credit ratings, and only proceed with changes after they are confident the change is permanent (Altman and Rijken, 2004; Hovakimian at al., 2009; Becker and Milbourn, 2011). A firm's labor productivity is likely to influence credit ratings in period t+1 because efficient managers are likely to efficiently allocate current assets; thus, superior managers have the ability to generate higher sales per level of input.

Using a combined sample of IG and NIG firms, we find a positive relation between the productivity of labor in period t and credit ratings in period t+1. The results suggest that managers of firms with higher credit ratings are able to achieve sales using a lower level of input. We conjecture that managers of firms with higher credit ratings demonstrate superior operational performance, planning, leadership, adaptability and corporate governance, and are therefore able to keep employment levels at their optimum to achieve the highest level of productivity. Thus, firms with maximum labor productivity have a comparative advantage compared to their peers. This comparative advantage is captured by credit rating agencies and is rewarded. Thus, after we control for business profile, size, stability, business risk, management quality, financial strength and corporate governance measures using predictive

validity techniques to establish the model with the highest explanatory power, we find that credit rating agencies are able to capture the influence of the productivity of labor and reward firms with higher credit ratings in the subsequent period.

Next, we divide our sample into IG and NIG firms. Whilst we find a positive relation between the productivity of labor in period t and credit ratings in period t+1 for IG firms, the relation is reversed in the NIG sample. An IG firm is likely to have the ability to keep sales at their optimum level. On the other hand, NIG firms are less likely to have the ability to increase sales to increase the productivity of labor; a NIG firm is more likely to decrease its number of employees to increase productivity. Overall, firms within a similar industry and similar risk levels are likely to utilize a similar number of employees per unit of output; thus, the number of employees per sales output is likely to remain stable. However, in periods of distress, riskier firms may reduce employee levels to increase revenue. The different relation between credit ratings in period t and labor productivity in period t+1 suggests credit rating agencies have the ability to capture the opportunistic behavior of NIG firms' corporate decision to increase profit/labor productivity at the expense of employee levels. A firm that reduces its employee levels to achieve short term gains is likely to cause a detrimental and permanent change in the labor force. Therefore, NIG firms that reduce employees (input) to increase the productivity of labor are more likely to experience a credit rating decrease in the subsequent periods. Our findings have important implication for market participants, regulators, credit rating agencies and other stakeholders in the capital market. For instance, bondholders could consider credit risk differently for IG and NIG firms using labor productivity information.

Our study may have some limitations. Our investigation is based in a South Korea setting; therefore, our findings may not be generalizable to other nations with different business environments. Furthermore, our main variable of interest, productivity of labor is calculated as sales per capita, which entirely relies on the number of employees, rather than the wage expense of employees. Therefore, our results may yield bias for 1) firms with a small number of highly paid employees, 2) firms that purchase shift work from outsourcing contractors, 3) capital intensive firms. However, even though, we fail to control for those specific firm characteristics, we find consistent results after controlling for firm fixed effects in our additional analysis. Moreover, the efficient market hypothesis would suggest that similar firms within a similar industry would take advantage of beneficial outsourcing opportunities. Therefore, over the entire sample, the influence is not considered significant. Thus, we find consistent evidence that credit ratings agencies reward IG firms with higher levels of labor efficiency. Moreover, we find consistent evidence suggests that credit rating agencies have the expertise to capture the opportunistic behavior of riskier firms.

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