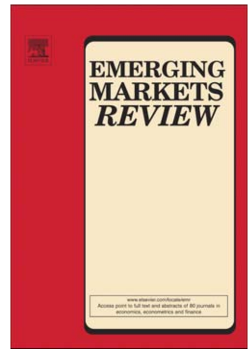

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PII: S1566-0141(17)30389-8
DOI: doi:10.1016/j.ememar.2017.10.002
Reference: EMEMAR 525

To appear in: *Emerging Markets Review*

Received date: 2 October 2017
Accepted date: 11 October 2017

Impact of Wage Rigidity on Sovereign Credit Rating

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Abstract

Sovereign credit rating is a condensed assessment of a country's ability to repay its public debt in a timely fashion. Downward wage rigidity has been considered a critical determinant of various macroeconomic and financial phenomena. This study examines the effect of a country's wage rigidity on its sovereign credit rating by directly measuring downward wage rigidities based on a regime-switching model. The results indicate that greater wage rigidity induces lower credit rating. We find that wage rigidity amplifies cash flow fluctuations and magnified cash flow volatility subsequently negatively affects the sovereign credit rating.

Keywords: wage rigidity, sovereign credit rating, regime switching, cash flow volatility

JEL classifications: E24, J31, G32, M41

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This paper was presented at the 2016 Cross Country Perspectives of Finance conferences held in Taiyuan and Pu'er, China.

1. Introduction

A sovereign credit rating (SCR) can be used to assess a country's ability to repay its public debt on time; it in return affects the interest rates of a country in the international financial market (Afonso et al., 2011; Chen et al., 2012). With the occurrence of various economic crises, the major credit-rating agencies have downgraded the SCR of a number of major countries (Bozic and Magazzino, 2013). In this context, the determinants of SCR have been at the core of macroeconomic research (Gültekin-Karakaş et al., 2011). A pioneering study by Cantor and Packer (1996) reports that SCR can be largely explained by various macroeconomic variables, including per-capita income, GDP growth, inflation, external debt, level of economic development, and default history. Previous studies have pinpointed other variables, such as investment-to-GDP ratio and foreign reserves (Afonso et al., 2011; Bissoondoyal-Bheenick, 2005). The growing body of recent literature has focused on labor market rigidities, such as labor market friction (Favilukis and Lin, 2013) and unemployment (Bai, 2015), as the core determinants of SCR.

The major credit-rating agencies have acknowledged the importance of labor market rigidities as a cause of corporate default. These agencies have incorporated labor market rigidities, as a key SCR measure, into their respective evaluation models. For instance, Moody's proposed in 2007 a default-forecasting model (i.e., the credit transition model) that measures the impact of macroeconomic conditions on default by using only two factors: the unemployment rate and the high yield spread of treasuries (Bai, 2015). Fitch Ratings also includes unemployment rate in its unique model (i.e., the sovereign rating model). However, although major credit-rating agencies assess the importance of labor market rigidities, only a few scholarships—save for those of Favilukis and Lin (2013) and Bai (2015)—discuss the impact of labor market rigidities on a country's credit rating.

Specifically, downward wage rigidity has been regarded as playing a crucial role among the labor market conditions, in terms of employment adjustment and unemployment (Batra, 2002; Beckerman, 1988; Dias et al., 2013; Fabiani et al., 2010; Favilukis and Lin, 2013; Grubb et al., 1983; Nickell et al., 2005). The literature on downward wage rigidity has explored various negative macroeconomic outcomes (Altonji and Devereux, 2000; Bauer et al., 2007; Beissinger and Knoppik, 2003; Chen and Zhang, 2007; Elsby, 2005; Fehr and Goette, 2005; Goette et al., 2007; Rhee and Song, 2013; Song et al., 2017). The negative impact of wage rigidity became even more important in the period during and after the recent recession (Doris et al., 2013). Our study grew out of conversations concerning this matter, especially where downward wage rigidity can be perceived as undesirable from the viewpoint of a country's credit rating.

This study investigates whether and how downward wage rigidity affects SCR, from a cross-national perspective. We address this issue throughout the following strategies. First, we directly measure a country's wage rigidity by employing a regime-switching econometric model. In estimating wage rigidity, we use firm-level sales data and quantify the responsiveness of wages to sales following Song et al. (2017). Then, we run the ordered probit regression of SCR on wage rigidity, as SCR is a discrete variable (Bozic and Magazzino, 2013). Finally, in exploring the linkage between wage rigidities and SCR, we allow the intervention of cash flow volatility. The rationale is that wage rigidity amplifies cash flow fluctuations (Schoefer, 2015) and that cash flow volatility subsequently affects credit risk (Acharya et al., 2012; Chowdhry and Schwartz, 2012; Emery, 1999; Scordis et al., 2008). Accordingly, we find some evidence of direct or dynamic effects of wage rigidity. First, we find that downward wage rigidity negatively affects SCR after controlling for other relevant factors. All the results from the alternative ordered response models are qualitatively similar. Second, by stages, we also observe that wage rigidity and cash flow volatility co-move; in turn, cash flow volatility erodes the SCR. These results are robust throughout a variety of estimation methods.

This paper makes four noteworthy contributions to the existing literature. First, despite the major credit-rating agencies acknowledging the importance of labor market rigidities, the academia has failed to duly address the role of wage rigidities as a determinant of SCR. Regarding this issue, we contribute to the existing literature by providing direct evidence for the impact of wage rigidities on SCR. Second, specific mechanisms linking wage rigidities to negative macroeconomic consequences are not well known in the existing literature. We thus take a step toward filling this void by showing that greater volatility of cash-surplus stemming from wage rigidities increases the possibility of insufficient internal reserves, thus leading to higher credit risk exposure. Finally, our findings shed light on the importance of wage rigidities from the perspective of macroeconomic health, thereby suggesting that policies aimed at labor market flexibility may have an important role in managing a country's credit risk.

The remainder of this paper is organized as follows. Section 2 presents our regime-switching-based measure for downward wage rigidity, using data from Compustat and the International Labour Organization (ILO). Section 3 describes the relationships among wage rigidity, cash flow volatility, and SCR, while focusing on theoretical models. Section 4 describes the data, and section 5 discusses the empirical findings. Finally, section 6 concludes.

2. Downward Wage Rigidity

2.1 Drawing on Wage Rigidity's Literature

Starting from the argument of Keynesian macroeconomics, there has been long-standing debate about whether wages are rigid.[1] Several empiricists have explored the existence of downward wage rigidities. Starting with McLaughlin (1994), the studies have examined the existence of downward wage rigidities by using micro-level data. Most studies suggest evidence of moderate degrees of wage rigidity (Beissinger and Knoppik, 2003; Chen and Zhang, 2007; Elsby, 2005; Fehr and Goette, 2005; Goette et al., 2007; Rhee and Song, 2013). In particular, Altonji and Devereux (2000) and using regime-switching specification wage rigidity, find that wages are almost completely rigid. Following the methodology of Altonji and Devereux (2000), Bauer et al. (2007) show evidence of real and nominal wage rigidity for the period 1975 to 2001 from West Germany. Also, Song et al. (2017) show a wide range of downward wage rigidity throughout the 19 countries.

2.2 Measuring Wage Rigidity

This study considers a regime-switching model to estimate wage rigidity, in line with Altonji and Devereux (2000) and Bauer et al. (2007). Hamilton (1989, 1990) first developed the regime-switching specification method to analyze structural shifts of time-series process conditioning, upon there being some changes to economic circumstances. The regime-switching approach supposes that the coefficients of regression models are subject to occasional discrete shifts, and thus estimates both the parameters that characterize the different regimes and the probability law for the transition between regimes. In running a simple linear regression, we consider a single slope parameter for the relevant regressor; however, in the current context of the regime-switching regression framework, we allow for the presence of two possibly different slopes for a given sample.

In this study, we apply the regime-switching method to the following regression of wage growth on sales growth:

$$\Delta wage_t = \gamma_0 + \beta_m \Delta sales_t + \sigma_m \varepsilon_t, \qquad m = 1, 2 \tag{1}$$

where $\Delta wage_t$ and $\Delta sales_t$ are the log differences of wage and sales in year t, respectively. As

[1] In a similar vein, the literature on cost accounting has addressed the downward sticky cost phenomenon using a firm-level analysis (Anderson et al., 2003; Balakrishnan et al., 2004, 2014; Balakrishnan and Gruca, 2008; Banker et al., 2013, 2014; Banker and Byzalov, 2013; Banker and Chen, 2006; Chen et al., 2012, 2013; Dierynck et al., 2012; Kama and Weiss, 2012; Yang, 2015). In particular, Dierynck et al. (2012) suggest the sticky behavior of labor costs (or wages) by using data from private firms in Belgium.

shown from $\sigma_m \varepsilon_t$, we assume that the error term variances are heterogeneous under different regimes. If the estimate for the slope parameter, β_m, in (1) is statistically significant, then this would imply that the wage growth rate flexibly responds to the sales growth rate. Then, we would match any significant estimate with a flexible wage regime. On the other hand, if we were to find the slope estimate derived in (1) not to be statistically significant, we would then match the estimate with a rigid wage regime. Hereafter, we assume that $m = 1$ and $m = 2$ represent the flexible wage and rigid wage regimes, respectively. That is, β_1 and β_2 indicate the slope parameters under flexible and rigid regimes, respectively.

The regression set up in (1) includes the sales growth rate as a regressor, rather than the gross domestic product (GDP) growth rate, which is used to measure wage rigidity (Bauer et al., 2007). The reason for using sales in place of GDP is that wages constitute a direct and major component of GDP in the national accounting: because of this, the regression of wage growth on GDP growth may be subject to a possible endogeneity problem.

To mitigate such a GDP-associated endogeneity problem, we collect firm-level sales data from the Compustat database and then obtain country-level average sales for use in regression (1). More than admittedly, firm sales relate to GDP via business cycle shocks and other common factors; firm-level sales, however, not so much directly comprise wage, as the country-level GDP directly relates to the wage in the national account.

To estimate those different slopes in (1) between the two regimes, we consider the following likelihood function for each individual observation in period *t*:

$$L_t(\boldsymbol{\beta}, \boldsymbol{\sigma}, \boldsymbol{\delta}) = \sum_{m=1}^{2} \frac{1}{\sigma_m} \Phi\left\{\frac{\Delta wage_t - \beta_m \Delta sales_t}{\sigma_m}\right\} P(s_t = m | \Omega_{t-1}, \boldsymbol{\delta_m}) \tag{2}$$

for $m = 1$ and 2 . $\Phi(\bullet)$ is the standard normal-density function and Ω_{t-1} represents the information set available in period $(t-1)$.[2] Under the two wage regimes, $\boldsymbol{\beta}$ is a (2 × 1) vector of the slope parameters $(\beta_1 , \beta_2)'$, and $\boldsymbol{\sigma}$ is a (2 × 1) vector of the error terms' standard deviations, $(\sigma_1 , \sigma_2)'$. More importantly, $P(s_t = m | \Omega_{t-1}, \boldsymbol{\delta_m})$ is the regime probability for regime *m*, representing a conditional probability that the state of the economy in period *t*, s_t, belongs to regime *m*. In the regime probability, the vector $\boldsymbol{\delta_m}$ parameterizes the past information $\Omega_{i,t-1}$ under regime *m*. Note that $\boldsymbol{\delta}$ on the left-hand side of (2) is $(\boldsymbol{\delta_1}' , \boldsymbol{\delta_2}')'$.

In this study, we further specify $P(s_t = m | \Omega_{t-1}, \boldsymbol{\delta_m})$ as

[2] For ease of discussion and simplicity of notation, we suppress the country index *i* in discussing the regime switching method in terms of time series, even though our main regressions use panel data.

$$P(s_t = m|\Omega_{t-1}, \boldsymbol{\delta}_m) = \frac{exp\{\delta_{m,0} + \delta_{m,1}\, I[\Delta wage_{t-1} < 0]\}}{\sum_{m=1}^{2} exp\{\delta_{m,0} + \delta_{m,1}\, I[\Delta wage_{t-1} < 0]\}} \qquad (3)$$

for $m = 1$ and 2. The regime probability in (2) is based on the logistic probability distribution. Note that $\boldsymbol{\delta}_m$ is a (2 × 1) vector of $(\delta_{m,0}\ ,\ \delta_{m,1})'$ under regime m. Additionally, $I[\Delta wage_{t-1} < 0]$ denotes a dummy variable for a negative value of wage growth rate in the previous period. As (3) implies, we assume that the regime probability, $P(s_t = m|\Omega_{t-1}, \boldsymbol{\delta}_m)$, is conditioned on $I[\Delta wage_{t-1} < 0]$ belonging to the past information set, Ω_{t-1}. Such an assumption is in keeping with previous studies (Bewley, 1999; Katz, 1986; Solow, 1979) that suggest that workers who experienced wage cuts in the previous period become more reluctant to repetitive wage cuts in the current period, and thus act more aggressively to deter continuous wage decreases.[3] Therefore, the probability that a rigid regime will occur in the current period is higher after a previous wage cut when the estimate for $\delta_{m,1}$ has a positive sign and is significant under the rigid wage regime.

Treating the regime probability $P(s_t = m|\Omega_{t-1}, \delta)$ as a weight, we can consider the likelihood function for each observation in (2) a weighted average of the standard normal-density functional values over the two regimes. If we take the log of the individual likelihood functions in (2) and sum those over the periods from 1 to *t*, we then obtain the following full likelihood function:

$$l(\boldsymbol{\beta}, \boldsymbol{\sigma}, \boldsymbol{\delta}) = \sum_{t=1}^{T} \log\left\{\sum_{m=1}^{2} \frac{1}{\sigma_m} \Phi\left\{\frac{\Delta wage_t - \beta_m \Delta sales_t}{\sigma_m}\right\} P(s_t = m|\Omega_{t-1}, \boldsymbol{\delta_m})\right\}. \qquad (4)$$

Note that $P(s_t = m|\Omega_{t-1}, \boldsymbol{\delta}_m)$ is specified by (2). We estimate the full likelihood function (4) by the maximum likelihood estimation and then substitute the resulting estimates for $\boldsymbol{\delta_m}$ into the regime probability in (3). Then, for each observation, we can calculate the regime probability that the associated observation in period *t* belongs to a particular regime. As a result, larger probabilities for the rigid wage regime would imply that the observed wage growth rates are more likely to exhibit more muted responses to the sales growth rates. In that sense, we use the estimated probability of a rigid regime as a measure of wage rigidity. Note that we parameterize $P(s_t = m|\Omega_{t-1}, \boldsymbol{\delta_m})$ as

[3] Based on the basic efficiency–wage hypothesis, Katz (1986) documents that employers may be quite reluctant to cut wages, even with an excess supply of labor, since reducing wages may actually lower productivity more than is proportionate and hence increase labor costs. Inversely, Solow (1979) suggests that increased wages improve morale and thus directly affect productivity through an increase in worker effort. Bewley (1999) concludes that the only reasonable theory of wage rigidity is the morale theory of Solow (1979), which emphasizes the adverse impact of wage cuts on morale, perceptions of fairness, and productivity.

$$P(s_t = m|\Omega_{t-1}, \boldsymbol{\delta_m}) = \delta_{m,0} + \delta_{m,1}\, I[\Delta wage_{t-1} < 0], \tag{5}$$

As aforementioned, the conditional probability specification in (5) implies that wage cut in previous periods are likely to affect current probability (Katz, 1986; Solow, 1979; Bewley, 1999).

With all the assumptions so far as, we specify wage growth rate as

$$\Delta wage_t = \gamma_0 + \gamma_1\, \Delta wage_{t-1} + \beta_{m,1} \Delta sales_t + \sigma_m \varepsilon_t \tag{6}$$

for two regimes, $m = f$ and r: f and r indicate flexible and rigid regimes, respectively. We include $\Delta wage_{t-1}$ as a regressor in (6) to control some possible autocorrelation and thus separate out the regime effects of $\Delta sales_t$ on $\Delta wage_t$. We also allow for heteroskedasticity in two regimes' error terms by including σ_m in (6). Among two slope estimates corresponding to each regime, an insignificant one represents rigid regime that implies weak response of wage growth rate to sales growth rate. whereas, a significant and positive estimate implies a flexible regime and further represents higher response of wage growth rate to sales growth rate.

3. Model Specifications

In this section, we develop the separate theoretical models following two-phase mechanisms: one is related to wage rigidity-cash flow volatility, and the other is to cash flow volatility-SCR. Then, we suggest our empirical models.

3.1 Phase I: Wage Rigidity to Cash Flow Volatility

As a first step, we explore the relationship between downward wage rigidity and national cash-surplus volatility by partially transforming Schoefer's (2015) model. Schoefer (2015) presents evidence of amplified cash flow fluctuations that stem from wage rigidity, postulating that wage rigidity may reduce recruitment by squeezing internal fund reserves.

Schoefer (2015) uses a simple version of the Diamond–Mortensen–Pissarides search-and-matching model and explains the relationships among wage rigidity, cash flow, and employment. Schoefer (2015) mainly considers the effects of wage rigidity on employment, especially under financial friction, whereas we view the model from a different perspective and suggest theoretical causality that runs from wage rigidity to cash flow fluctuation. To envisage the relationship between wage rigidity and cash flow volatility, we present the following model, which aligns with Schoefer (2015). An individual firm chooses an optimal level of employment n by considering

$$max_{\{n\}}\ \beta\,(z - w)n - c(n), \tag{7}$$

where w and z indicate wage and productivity, respectively. Further, we assume that wage, w, is a function of productivity shock, z; furthermore, we assume that wage w is a function of productivity shock z. The model implicitly assumes that wage is a function only of z, productivity shock, which is purely exogenous to the firms considered in the model. Therefore, from the standpoint of firms, the wage that is a function only of exogenous shock z is also considered an exogenous variable to firms: the productivity shock is not under the control of firms, but rather is exogenously given. Therefore, for their employees, firms make decisions regarding only employment n, not wage w. This feature also implies that the derivative of wage with respect to productivity shock is to be calculated not by firms, but by some sort of third party. Differentiating wage with respect to the shock is part of the comparative analysis process.

In addition, $c(n)$ represents all the relevant hiring costs, save for wage payment wn. β denotes the time discount rate, which is less than 1 but is often close to 1. For the maximization problem in (7), the first-order condition with respect to employment n is

$$c'(n) = \beta\ (z - w),$$

where $c'(n)$ represents the first derivative function of the hiring cost function, $c(n)$. By rearranging and differentiating the above first-order condition with respect to the productivity shock z, we obtain

$$\left(\frac{\partial n}{\partial z}\right) = \frac{\beta}{c''}\left\{1 - \left(\frac{\partial w}{\partial z}\right)\right\}, \tag{8}$$

where $c''(n)$ represents the second derivative function of hiring cost function, $c(n)$.

As $(\partial w/\partial z)$ and $(\partial n/\partial z)$ imply in (8), we follow Schoefer (2015) and allow wage w and employment n to depend on productivity z, to consider the procyclicality of employment and wage. In the current context, procyclicality implies that employment and wage positively co-move with the business cycle, z. In particular, when a wage is highly procyclical, this means that the wage is largely flexible in responding to the business cycle; this, correspondingly, implies large absolute values for $(\partial w/\partial z)$.

Following Schoefer (2015), we regard $(z - w)n$—that is, output minus wage payment—as cash flow. Note that n is the optimal level of employment chosen by the firm. To discuss a relationship between wage rigidity and cash flow volatility, we conduct the following analysis. First, we differentiate the cash flow $CF = (z - w)n$ with respect to z and then observe

$$\left(\frac{\partial CF}{\partial z}\right) = \left\{1 - \left(\frac{\partial w}{\partial z}\right)\right\} n + (z - w)\left(\frac{\partial n}{\partial z}\right). \tag{9}$$

Plugging (8) into (9) and using the first-order condition, $c'(n) = \beta\ (z - w)$, we obtain

$$\left(\frac{\partial CF}{\partial z}\right) = \left\{n + \left[\frac{c'(n)}{c''(n)}\right]\right\}\left\{1 - \left(\frac{\partial w}{\partial z}\right)\right\}. \tag{10}$$

Equation (10) illustrates the relationship between $\left\{1 - \left(\frac{\partial w}{\partial z}\right)\right\}$, which is wage rigidity, and $(\partial CF/\partial z)$, which is cash flow volatility. According to (10), the effect of $\left\{1 - \left(\frac{\partial w}{\partial z}\right)\right\}$ on $(\partial CF/\partial z)$ can be exaggerated or attenuated by the magnitude of $\left\{n + \left[\frac{c'(n)}{c''(n)}\right]\right\}$. A possible interpretation for (10) is that the level of employment n affects the relationship between wage rigidity $\left\{1 - \left(\frac{\partial w}{\partial z}\right)\right\}$ and cash flow volatility $\left(\frac{\partial CF}{\partial z}\right)$. In particular, under a higher employment level, the wage rigidity more significantly affects cash flow volatility. Such a relationship is consistent with the previously derived outcome in (10).

3.2 Phase II: Cash Flow Volatility to SCR

The next step is to link cash flow fluctuation to credit risk. The related literature shows that high cash flow volatility induces insufficient internal funds, thereby forcing firms to become exposed to credit risk and liquidity problems (Chowdhry and Schwartz, 2012; Emery, 1999; Scordis et al., 2008).[4]

We introduce two propositions by meticulously modifying the model proposed by Acharya et al. (2012). In line with that study, we assume a firm with an outstanding debt and a single asset that yields cash flow in each period. The cash flow at each of t = 0 and t = 2 is assumed to be fixed at constant levels, but the flow at t = 1 is the sum of the expected level $\overline{x_1}$ and the zero-mean random cash flow shock u.

In the model, a firm with an inherited debt can either invest its cash for the long term, or retain it as a cash buffer until that debt comes due. At date 0 (i.e., the initial stage), the firm allocates its cash flow at date 0, x_0, to either investment, I, or cash-holding, c. At date 0, the investment is made for the return, $f(I)$, which is yielded at date 2 (i.e., the final stage). On the other hand, at date 0, cash is reserved to preclude any default that could occur at date 1 (i.e., the assumed debt matures at date 1).

A larger volume of retained cash holdings implies lower investment; it thus reduces future cash flows as the part of investment return that would be expected at date 2. On the other hand, a larger cash reserve at date 0 would reduce the probability of a cash shortage at date 1, and thus

[4] Anticipating higher shareholder value, the theory advocates a smooth cash flow (Froot et al., 1993; Smith and Stulz, 1985). Breeden and Viswanathan (1998), DeMarzo and Duffie (1995), and Goel and Thankor (2003) show that lower cash flow volatility can help outsiders assess firm value. In this context, Chowdhry and Schwartz (2012) advocate smooth cash flows and thus emphasize hedging policies.

increase the likelihood that the firm survives until date 2 to reap the benefits of the long-term investment. The firm's optimal cash and investment policies balance these costs and benefits of holding cash. The outcome of choosing between cash-holding and investment determines the market value of debt initially inherited by the firm. In the model, the market value of debt *D* is equal to the face value of debt *B*, adjusted for the loss that creditors expect to incur in default and thus inversely related to the credit spread.

At date 0, the firm makes its decision regarding investment versus cash-holding, according to two different motivations. First, a firm has a precautionary motivation to hold more cash currently at date 0, to reduce the probability of debt in the next stage (i.e., date 1). As the lower bound of cash flow shock at date 1, $\underline{u}$, further decreases (recall that we assume $\underline{u} < 0$), the downside risk to cash flow at date 1 becomes higher and thus gives rise to the precautionary motivation. Motivated by precautionary cash-holding, the firm reduces its investment and instead sets aside more cash at date 0 to preclude default risk at date 1. Therefore, under the precautionary motivation, a decrease in the lower limit of cash flow shock at date 1 reduces the investment made at date 0. As a result, the investment *I* co-moves with $\underline{u}$, the lower limit of cash flow shock in the same direction, and thus implies a positive $\frac{\partial I}{\partial \underline{u}}$.

Second, in choosing investment at date 0, a firm can be motivated in ways different from those seen with the precautionary motivation. Suppose that, at the current stage, a firm is certain that it can avoid debt default at the next stage: the firm is then no longer motivated to hold cash on a precaution; rather, it desires to maximize its payoff over all the dates, without concern for default at date 1. Making a larger investment is more advantageous to the firm, since the investment is assumed to guarantee a deterministic return at date 2. Therefore, at date 1 (i.e., the middle stage), a smaller size of bottom cash flow shock $\underline{u}$ implies a greater likelihood of smaller cash flow. To compensate for the smaller cash flow at date 1, the firm makes a larger investment at date 0 (i.e., the current stage), in order to derive a larger return at date 3 (i.e., the final stage). As a result, the smaller $\underline{u}$ results in an increase in investment, *I*, and thus implies that the sign of $\frac{\partial I}{\partial \underline{u}}$ is negative.

Here, we specify the theoretical model. We consider the cash flow shock for the interval $[\underline{u}, \bar{u}]$, where $\underline{u}$ and $\bar{u}$ denote the lower and upper bounds of cash flow shocks, respectively. This feature arises from the assumption that the minimum cash flow shock is sufficiently large to rule out the existence of unlimited liability (Acharya et al., 2012). To maintain the zero-mean assumption, the upper bounded cash flow shock $\bar{u}$ is assumed to have the same value as the lower bounded cash flow $\underline{u}$, except that the former has a positive value and the latter a negative one. The hazard rate for the firm is defined as

$$h(u) = \frac{g(u)}{1 - G(u)}, \tag{11}$$

where $g(u)$ denotes the probability distribution function of cash flow shock u and $G(u)$ denotes the cumulative distribution function.

At time $t = 0$, the firm borrows and invests. The associated debt matures at time $t = 1$ and the investment outcome is realized at time $t = 2$. The asset is assumed to generate cash flow x_0 at time $t = 0$. We define the default boundary as

$$u_B = B - x_0 + I - \overline{x_1}, \tag{12}$$

where B denotes the debt's face value. By u_B, we denote the minimum cash flow shock that allows the firm to repay the debt in full and thus preclude default.

The market value of equity is

$$E = \int_{u_B}^{\overline{u}} [x_o - I + \overline{x_1} + u - B + f(I) + x_2]\, g(u) du,$$

where $f(I)$ denotes the investment return. To maximize the equity value, at date 0, the firm chooses the optimal investment that satisfies the following first-order condition:

$$\frac{\partial E}{\partial I} = \int_{u_B}^{\overline{u}} [-1 + f'(I)] g(u) du - [x_o - I + \overline{x_1} + u_B - B + f(I) + x_2] g(u_B) \frac{du_B}{dI} = 0.$$

Using the definition of the default boundary in (12) and rearranging it, we obtain

$$f'(I) = 1 + (f(I) + x_2)\, h(u_B), \tag{13}$$

where $f'(I)$ denotes the marginal return of investment. In addition, the market value of the firm's outstanding debt, D, is

$$D = B - \int_{\underline{u}}^{u_B} [B - (c + \overline{x_1} + u) g(u)] du.$$

Additionally, we define the credit spread, s, as

$$s = \frac{B}{D} - 1.$$

Recall that B and D denote the face value and market value of debt, respectively. The credit spread is one of the most popular measures of credit risk.

To illustrate the relationship between cash flow volatility and credit risk, this study assumes a uniform distribution for cash flow shock u in the interval $[\underline{u}, \overline{u}]$. For the uniform distribution, the probability density function $g(u)$ and cumulative distribution function $G(u)$ are defined as follows:

$$g(u) = \frac{1}{\bar{u} - \underline{u}}, \quad G(u) = \frac{u - \underline{u}}{\bar{u} - \underline{u}}.$$

Then, we define the hazard rate function as

$$h(u) = \frac{g(u)}{1 - G(u)} = \frac{1}{\bar{u} - u}. \tag{14}$$

Since the upper and lower bounded cash flow shocks are of the same magnitude (but with opposite signs), we observe $\bar{u}\underline{u} < 0$ and $|\bar{u}| = |\underline{u}|$. According to the definition of u_B in (12) and (14), we have

$$h(u_B) = \frac{1}{\bar{u} - u_B} = \frac{1}{\bar{u} - M - I} = -\frac{1}{\underline{u} + M + I}, \tag{15}$$

where M denotes $(B - x_0 - \overline{x_1})$. Substituting (15) into the first-order condition in (13) and rearranging it, we obtain

$$1 = f'(I) + \left[\frac{f(I) + x_2}{\underline{u} + M + I}\right]. \tag{16}$$

By taking the derivative of (16) with respect to $\underline{u}$ and rearranging it, we obtain

$$\frac{\partial I}{\partial \underline{u}} = \frac{f(I) + x_2}{\left(\underline{u} + M + I\right)^2 f''(I) + \left(\underline{u} + M + I\right) f'(I) - f(I) - x_2}, \tag{17}$$

where $f''(I)$ denotes the second derivative of $f(I)$.

We assume that the investment function $f(I)$ takes the log form, $f(I) = \alpha + log(I)$, where the sign of α is assumed to be positive. Using the definitions of $f(I)$ and u_B, (17) can be expressed as

$$\frac{\partial I}{\partial \underline{u}} = \frac{\alpha + log(I) + x_2}{\frac{(\underline{u} + u_B)}{I}\left\{-\frac{(\underline{u} + u_B)}{I} + 1\right\} - \alpha - log(I) - x_2}. \tag{18}$$

Now, we examine the market value of the firm's outstanding debt, to consider the effect of $\underline{u}$ on debt. We denote $\int_{\underline{u}}^{u_B} [B - (c + \overline{x_1} + u) g(u)] du$ as L. Recall that $c = x_0 - I$. Using $c = x_0 - I$ and the uniform distribution of u, we have

$$L = \frac{\left(M + I - \underline{u}\right)^2}{-4\underline{u}}. \tag{19}$$

Taking the derivative of (19) with respect to $\underline{u}$, we have

$$\frac{\partial L}{\partial \underline{u}} = \left[\frac{M + I - \underline{u}}{2\underline{u}}\right]\left\{\left[\frac{M + I}{2\underline{u}}\right] + \frac{1}{2} - \left(\frac{\partial I}{\partial \underline{u}}\right)\right\} = \left[\frac{u_B - \underline{u}}{2\underline{u}}\right]\left\{\left[\frac{u_B + \underline{u}}{2\underline{u}}\right] - \left(\frac{\partial I}{\partial \underline{u}}\right)\right\}. \tag{20}$$

The second equality of (20) uses the definition of the default boundary, $u_B \equiv M + I$, where M is equal to $B - x_0 - \overline{x_1}$.

Furthermore, we perform several simulations to calculate and check the signs of $\left(\frac{\partial I}{\partial \underline{u}}\right)$ and $\left(\frac{\partial L}{\partial \underline{u}}\right)$, according to (18) and (20), respectively. To this end, we simulate a set of components of $\left(\frac{\partial I}{\partial \underline{u}}\right)$ and $\left(\frac{\partial L}{\partial \underline{u}}\right)$ from the first-order condition for the optimal investment, $1 = f'(I) + \left[\frac{f(I)+x_2}{\underline{u}+M+I}\right]$ in (16). For the simulations, we assign various values to M, x_2, and I and generate a set of combinations of $\underline{u}$, $\bar{u}$, and u_B that satisfy the first-order condition. For simulation purposes, we still consider the assumption for $f(I) = \alpha + log(I)$. Using the values for M, x_2, $\underline{u}$, $\bar{u}$, u_B, and I, we calculate and check the signs of $\left(\frac{\partial I}{\partial \underline{u}}\right)$ and $\left(\frac{\partial M}{\partial \underline{u}}\right)$ according to the condition in (17) and (18), respectively.

<u>*Proposition 1*</u>: The sign of $\frac{\partial I}{\partial \underline{u}}$ is nonpositive under the assumptions of (i) the log investment function, (ii) the uniform distribution of cash flow shock, and (iii) the positive sign of $(\underline{u} + M)$.

Since $\underline{u}$ represents the lower bounded cash flow shock and the cash flow shock follows a symmetrically uniform distribution with a zero mean, Proposition 1 implies that greater cash flow volatility will increase the optimal investment level.

As shown in Appendix (B), the simulation results show that the sign of $\left(\frac{\partial I}{\partial \underline{u}}\right)$ is negative as long as (i) the minimum cash flow shock $\underline{u}$, (ii) the maximum cash flow shock $\bar{u}$, and (iii) the default boundary u_B all satisfy $\underline{u} < u_B < \bar{u}$. Under the third of these conditions (among others), a firm chooses the optimal levels of investment and thus of cash-holding. Unless the condition for $\underline{u} < u_B < \bar{u}$ holds, the optimal choice for investment and cash is not economically meaningful, since a firm will either always default or never default. Excluding those cases, we concern ourselves with the case of $\underline{u} < u_B < \bar{u}$. The simulation results confirm that the sign of $\left(\frac{\partial I}{\partial \underline{u}}\right)$ for as many as possible incidences is negative under the condition of $\underline{u} < u_B < \bar{u}$, and thus supports Proposition 1 (which claims $\frac{\partial I}{\partial \underline{u}} < 0$).

<u>*Proposition 2*</u>: The sign of $\left(\frac{\partial L}{\partial \underline{u}}\right)$ is negative under optimal investment, given the assumptions of (i) the log investment function, (ii) the uniform distribution for cash flow shock, and

(iii) sufficiently negative values for $\underline{u}$.

Excluding the trivial case for $u_B = \underline{u}$, we observe $u_B - \underline{u} > 0$, since $\underline{u}$ is the lower bound for the cash flow shock at date 1. Additionally, $\underline{u}$ takes a negative sign, since it is the lower bound of random shocks symmetrically distributed around the zero mean. As a result, $\left[\frac{u_B-\underline{u}}{2\underline{u}}\right]$ on the right-hand side of the second equality in (20) always takes a negative sign. Then, the sign of $\left(\frac{\partial L}{\partial \underline{u}}\right)$ in (20) depends on that of $\left\{\left[\frac{u_B+\underline{u}}{2\underline{u}}\right] - \left(\frac{\partial I}{\partial \underline{u}}\right)\right\}$ on the right-hand side of the second equality in (20): the sign of $-\left(\frac{\partial I}{\partial \underline{u}}\right)$ is positive because of Proposition 1. Therefore, the sign of (20) depends on that of $\left[\frac{u_B+\underline{u}}{2\underline{u}}\right]$ and thus $(u_B + \underline{u})$. Excluding the trivial case for $u_B = 0$, we have cases either for $u_B > 0$ or for $u_B < 0$.

First, consider $u_B > 0$. Recalling that we consider the case for $\underline{u} < u_B < \bar{u}$, $u_B > 0$ implies $0 < u_B < \bar{u}$. In terms of absolute values, the latter inequality can be expressed as $0 < |u_B| < |\bar{u}|$, and thus $0 < |u_B| < |\underline{u}|$: the cash flow shocks are symmetrically distributed over the interval, $[\underline{u}, \bar{u}]$, centered by the zero mean. The inequality, $0 < |u_B| < |\underline{u}|$, with $u_B > 0$ and $\underline{u} < 0$ implies that $(u_B + \underline{u})$ is less than 0. This feature implies that $\left[\frac{u_B+\underline{u}}{2\underline{u}}\right] > 0$ with $-\left(\frac{\partial I}{\partial \underline{u}}\right)$ > 0 together results in $\left\{\left[\frac{u_B+\underline{u}}{2\underline{u}}\right] - \left(\frac{\partial I}{\partial \underline{u}}\right)\right\} > 0$. The latter inequality, when combined with $\left[\frac{u_B-\underline{u}}{2\underline{u}}\right] <$ 0, leads to the negative sign of $\frac{\partial L}{\partial \underline{u}}$ in (20).

Second, consider $u_B < 0$. Then, we have $(u_B + \underline{u}) < 0$ combined with $\underline{u} < 0$. $\left\{\left[\frac{u_B+\underline{u}}{2\underline{u}}\right] - \left(\frac{\partial I}{\partial \underline{u}}\right)\right\} > 0$ with $-\left(\frac{\partial I}{\partial \underline{u}}\right) > 0$ together. Recall that $\left[\frac{u_B-\underline{u}}{2\underline{u}}\right]$ on the right-hand side of the second equality in (20) always takes a negative sign: $\frac{\partial L}{\partial \underline{u}}$ in (20) takes a negative sign, and Proposition 2 holds. In summary, once Proposition 1 holds, then Proposition 2 should also hold.

Finally, the negative sign of $\left(\frac{\partial L}{\partial \underline{u}}\right)$ in Proposition 2 implies a positive sign for $\left(\frac{\partial D}{\partial \underline{u}}\right)$, according to the aforementioned definition of debt market value D—that is, $D = B - L$, where B is a given level of face value of debt. The positive sign of $\left(\frac{\partial D}{\partial \underline{u}}\right)$ implies that a smaller absolute size of negative $\underline{u}$—that is, a larger value of $\underline{u}$—enlarges the market debt value D, and thus reduces the credit spread s, the latter of which is defined as $\frac{B}{D} - 1$ for a given value of B. Finally, Proposition 2 suggests that a lower volatility of cash flow shocks—that is, a smaller absolute size for $\underline{u}$—can reduce the credit spread and thus improve the credit rating, which in turn implies an inverse relationship between cash flow volatility and SCR.

3.3 Empirical Models

The existing literature on sovereign country risk—especially the study of Favilukis and Lin (2013)—mostly uses simple linear regressions while assuming that differences between two adjacent rating categories are identical. For this reason, Bozic and Magazzino (2013) assert that any difference tends to follow a nonlinear structure rather than a linear representation; they employ a nonlinear transformation of ratings by using logistic and exponential functional forms.[5] However, such a nonlinear transformation still has limitations: in particular, the associated results are sensitive to the assumed functional forms for the nonlinear transformation.

To preclude the aforementioned biases, we employ both ordered probit and logit models to examine the effect of wage rigidity on SCR. Ordered probit and logit regressions belong to certain kinds of ordered response models that are frequently used to deal with a variety of discrete dependent variables (e.g., bond ratings, schooling attainment, or election voting). Admittedly, the ordered response model is influenced by the probability distribution of the latent variables that underlie the discrete dependent variables. Despite their dependence on the assumed distribution, ordered response models in the current context are distinct, in that they treat a credit rating as an ordinal rather than cardinal measure; this is considered in the linear and nonlinear approximations.[6]

Here, let us suppose that discrete dependent variable y belongs to one of J categories—that is, $y \in \{1, 2, \cdots, J\}$—and that there are k regressors represented by the $(k \times 1)$ vector, x. Then, we assume that the cumulative probabilities of the discrete categories relate to a single index of explanatory variables, in the following way.

$$\Pr[y \leq j \,|x] = F\left(k_j - x'\beta\right), \qquad j = \{1, 2, \cdots, J\} \tag{21}$$

where a scalar k_j characterizes the jth among J categories and a $(k \times 1)$ vector β denotes coefficient parameters for the k regressors. F represents the cumulative distribution function of $(k_j - x'\beta)$. F for the standard normal and logistic distributions specifies the ordered probit and

[5] Prior to Bozic and Magazzino (2013), Afonso (2003) and Reisen and von Maltzan (1999) examine the determinants of SCR by employing the nonlinear transformation of ratings.

[6] In the same vein, Afonso et al. (2009), Gaillard (2009), and Bissoondoyal-Bheenick et al. (2005) use a discrete choice approach to analyze the determinants of SCR.

logit regressions, respectively.

We incorporate our key regresssor WR_{it} and the aforementioned control variables into the ordered response regression models as follows:

$$SCR_{it} = \beta_0 + \beta_1 WR_{it} + \beta_2 GNI_{it} + \beta_3 CA_{it} + \beta_4 ND_{it} + \beta_5 INTR_{it} + \beta_6 NFA_{it} + \varepsilon_{it}. \quad (22)$$

WR_{it} represents the wage rigidity measure, which is calculated through the regime-switching model, and SCR_{it} is the scaled value of sovereign credit risk. Following Afonso et al. (2011), we consider GNI_{it}, CA_{it}, ND_{it}, $INTR_{it}$, and NFA_{it} a group of control variables. GNI_{it}, CA_{it}, ND_{it}, $INTR_{it}$, and NFA_{it} represent per-capita gross national income (GNI), current account balance, national debt, interest rate, and net financial account, respectively.

The aforementioned theoretical motivation suggests that wage rigidity affects SCR via the channel of cash flow volatility. For this reason, we perform two subregressions to explore the theoretical channel. First, we start with the following regression:

$$CFV_{it} = \gamma_0 + \gamma_1 WR_{it} + \gamma_2 N_{it} + \varepsilon_{it}^2, \quad (23)$$

where CFV_{it} denotes cash flow volatility for country i at year t. Regression (23) is motivated by the previously derived relation $(\partial CF/\partial z) = (n + \omega)\{1 - (\partial w/\partial z)\}$. Regression (23) aims to test for the presence of a linkage from wage rigidity WR_{it} to cash flow volatility CFV_{it}. As a regressor in regression (23), we include employment N_{it} to reflect employment underlying $(n + \omega)$ in the condition $(\partial CF/\partial z) = (n + \omega)\{1 - (\partial w/\partial z)\}$. Since we trace from wage rigidity to credit rating via cash flow volatility, we first calculate the fitted value of CFV_{it} from regression (23), and next use the resulting metric $\widehat{CFV}_{it}$ in the ordered probit and logit regressions:

$$SCR_{it} = \delta_0 + \delta_1 \widehat{CFV}_{it} + \delta_2 GNI_{it} + \delta_3 CA_{it} + \delta_4 ND_{it} + \delta_5 INTR_{it} + \varepsilon_{it}^3. \quad (24)$$

All the regressors other than $\widehat{CFV}_{it}$ in (24) are identical to the control variables in (22). Indeed, the only difference between regressions (22) and (24) is that (24) includes $\widehat{CFV}_{it}$, while (22) includes WR_{it}.

4. Data

In this section, we provide detailed information regarding the sample data used in our empirical analysis. First, considering the role of sales as a driver of wages, we apply the country-average of firm-level sales, consistent with Song et al. (2017). During the period from 2000 to 2013, the firm-level sales data comprises 410,012 firm-level observations that were listed on the stock markets of 19 countries (i.e., Australia, Brazil, Canada, China, Germany, Hong Kong, India, Indonesia, Japan, Malaysia, the Netherlands, Philippines, Poland, Russia, Singapore, South Korea, Thailand, the United Kingdom, and the United States). The firm-level sales data is obtained from the Compustat Annual Industrial Database.

Second, we collect wage data of the 19 countries from the ILO statistics databases, also during the 2000–2013 period. We assume that, from the employer perspective, wages constitute the only cost of hiring workers: we assume that no recruiting and job-matching costs translate into any cost to the employers. Wage data are extracted from the earnings data found in the ILO statistics and databases.[7] Since ILO wage data are sampled monthly, we multiply the wage data by 12 to make those data comparable to the annual data available for the other variables. Essentially, our wage data comprised the average monthly wage, which is sourced from the ILO. Wage data are defined as previously discussed: the ILO definition of "wage" takes into account (i) direct wages and salaries, (ii) remuneration for time not worked (excluding severance and termination pay), and (iii) bonuses and gratuities. Conclusively, our ILO wage data comprise the country-level averages of surveyed wages collected from employers and employees in individual countries. In this respect, the wage data used in this study are in the country dimension, although they are collected from firms within each country. Appendix (A) provides more details on the wage data, consistent with that of Song et al. (2017).

Third, we construct the SCR variable in the following way. We adopt the long-term foreign currency ratings publicly provided by Fitch Ratings—namely, AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-, and CCC. We leverage information concerning outlook-watch categories (i.e., positive, stable, and negative) and categorize each rating into one of three classes (i.e., positive, stable, and negative). As a result, we derive 51 credit rating groups and assign numerical values to each group: 1 for the lowest rating group (i.e., the CCC negative group) and 51 for the highest Fourth, we define the cash flow variable rating group (i.e., the AAA positive group).

Fourth, we define the cash flow as comprising revenue (including grants) minus expense, minus net acquisition of nonfinancial assets; we express the resulting value as a percentage of each country's GDP. Positive and negative cash flow signs indicate cash surpluses and deficits, respectively. The World Bank Indicator database is our data source for cash flow. To calculate cash flow volatility, we apply the GARCH(1,1) model to the annual time series data of cash flow

[7] According to the ILO, earnings data includes information on the following wage statistics: gross remuneration in cash and kind, which is paid to employees as a rule at regular intervals for time worked or work done; this is paid together with remuneration for time not worked, such as annual vacation, or other types of paid leave or holidays. (See the ILO's definitions of statistical concepts and its database at www.ilo.org.)

for each country; we then use the estimated conditional variance as the measure of cash flow volatility.[8]

Finally, other variables including GNI, employment, current accounting surplus, national debt, real interest rate, and net-financial account are discussed as follows. *Per-capita GNI* is based on purchasing power parity (PPP). PPP GNI is GNI converted to international dollars by using PPP rates. (An international dollar has the same purchasing power over GNI as the USD has in the United States.) GNI is the sum of value added by all resident producers, plus any product taxes (less subsidies) not included in the valuation of output, plus net receipts of primary income (compensation of employees and property income) from abroad. Data are in current international dollars based on the 2011 International Comparison Program round. Then, *employment* data comes from the ILO database. We calculate the unemployment rate by dividing the number of unemployed persons by the size of the working-age population. We then subtract the resulting rate from 1 to obtain the employment rate variable. The ILO defines the unemployed and working-age populations as follows. The ILO defines unemployed persons as all persons of working age who were not in paid employment or self-employment during the reference period; were available for paid employment or self-employment during the reference period; and had taken specific steps in a specified recent period to seek paid employment or self-employment.[9] The ILO defines the working-age population comprising persons aged 15 years and older.[10] Meanwhile, *the current account surplus* is the sum of net exports of goods and services, net primary income, and net secondary income. The data are in current USD. *National debt* is an aggregate stock of direct government fixed-term contractual obligations to domestic and foreign units, and it is calculated as of the last day of the fiscal year. Debt includes domestic and foreign liabilities, including currency and money deposits, securities other than shares, and loans. The *real interest rate* is the lending interest rate adjusted by the GDP deflator. Importantly, the *net financial account* indicates the net acquisition and disposal of financial assets and liabilities, and it measures how net lending to (or borrowing from) nonresidents is financed. In principle, the net financial account is equal to the sum of the balances on the current and capital accounts.

Table 1. Summary statistics.

Study Period: 2000–2013	Mean	Median	Standard	25%	75%

[8] Although the sample period (2000–2013) is rather short for the GARCH estimation, the GARCH-type conditional variance is better than other alternatives, given data availability.

[9] Refer to the ILO homepage (www.ilo.org) for further descriptions regarding the job-seeking process.

[10] The legal definition of “working age” varies by country.

Sample Observations: 266			Deviation		
Sovereign Credit Rating Score	36.16	38	12.85	26	50
Wage Rigidity	-0.758	0.002	0.180	0.180	0.004
Cash Flow (millions of USD)	-1.561	-2.111	3.616	-3.760	0.352
Per-capita GNI (USD)	21035	19970	17863	3410	37150
Current Account (millions of USD)	-2421	8852	149260	-18605	34801
National Debt (millions of USD)	1528071	293943	3141906	106714	1100000
Real Interest Rate (%)	5.177	4	8.660	2	5
Net Financial Account (millions of USD)	-3486	7911	145398	-20060	31519

Notes: This table presents the estimates for the regime-switching regression in (6). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5. Empirical Results

5.1 Estimates of Regime-switching Regression

In Table 2, we present the estimation results for the regime-switching regression in (6), using the data for 19 sample countries.[11] According to the results, we observe the two distinguishable slope estimates: one slope estimate is insignificant while the other is significantly positive. This feature implies that there exist two different regimes regarding the response of wage growth rate to sale growth rate. Consequently, describing that the rigid regime is substantially distinguished from the flexible regime, the result suggests the pervasiveness of downward wage rigidity.

Table 2. Regime-switching regression of wage growth on sales growth.

Regime	Dependent Variable	Independent Variable	Coefficient Estimate	z-Statistic
Rigid Slope	$\Delta wage_{it}$	$\Delta sales_{it}$	-1.085	-0.822
Flexible Slope	$\Delta wage_{it}$	$\Delta sales_{it}$	0.011^{**}	2.435
Regime	**Probability Regressor**		**Coefficient Estimates**	**z-Statistic**
Flexible Slope	$I(\Delta wage_{it} < 0)$		-1.353^{**}	-2.146

Notes: This table technically reports the coefficient estimate for $I(\Delta wage_{it} < 0)$ representing the flexible regime. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In addition to the two slope parameters, we also report the estimates for the parameters that is implemented for $I(\Delta wage_{t-1} < 0)$. The significantly negative estimate for $I(\Delta wage_{t-1} < 0)$ suggests that a prior wage cut inversely affects the flexible regime probability ($p_f = 1 - p_r$) and thus positively impacts the probability for rigid regime (p_r). Such a positive association between

[11] The result of Table 2 is same to that of Song et. al (2017) since both studies use the same wage-sales data.

a previous wage cut and rigid regime probability is consistent with the efficiency-wage theory. Thus, employees who have experienced recent wage cut tend to be resistant to onward wage cuts, increasing the probability for rigid regime of wage response to sales. Overall, our results suggest the pervasive incidence of downward wage rigidities across the 19 sample countries.

5.2 Direct Association between Wage Rigidity and SCR

Table 3 reports the estimation results for the ordered probit and logit regressions in (22), using panel data. All the coefficient estimates for the wage rigidities by ordered probit and logit panel regression are negative and statistically significant at the 1% level. This feature is consistent with our expectation that higher wage rigidity explains a lower SCR. Among those control variables, the coefficient estimates for national debt and interest rate are negative and statistically significant at the 1% level; on the other hand, estimates for the current account and net financial account balance are not statistically significant. The estimates for the current account balance are analogous to those of Bozic and Magazzino (2013), suggesting that the current account balance is less relevant to the credit rating, relative to other types of fundamental factors.

Table 3. The results of panel regression by using the ordered response model.

Panel A. Ordered Probit Regression

Model	Coefficient	Standard Error	*z*-Statistic	*P*-Value
WR	-0.638	0.276	-2.320	0.020**
GNI	0.000	0.000	14.750	0.000***
CA	0.000	0.000	0.100	0.918
ND	0.000	0.000	-5.820	0.000***
INTR	-0.034	0.008	-4.180	0.000***
NFA	0.000	0.000	-0.060	0.951
Number of Observations: 266				
Log Pseudo Likelihood: -540.31541	Pseudo R-square: 0.2868			
Wald Chi-square Statistic: 255.22	Probability > Chi-square Statistic: 0.0000			

Panel B. Ordered Logit Regression

Model	Coefficient	Standard Error	*z*-Statistic	*P*-Value
WR	-0.860	0.370	-2.320	0.020**
GNI	0.000	0.000	12.310	0.000***
CA	0.000	0.000	-0.100	0.921
ND	0.000	0.000	-5.380	0.000***
INTR	-0.065	0.016	-4.150	0.000***
NFA	0.000	0.000	0.050	0.961
Number of Observations: 266				
Log Pseudo Likelihood: -538.57249	Pseudo R-square: 0.2891			
Wald Chi-square Statistic: 222.00	Probability > Chi-square Statistic: 0.0000			

Notes: This table presents both ordered probit and logit panel regressions, with controls for the relationship between wage rigidities and SCR. GNI_{it}, CA_{it}, ND_{it}, $INTR_{it}$, and NFA_{it} represent per-capita GNI, current account balance, national debt, interest rate, and net financial account, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All standard errors are calculated by using the robust covariance method.

Moreover, to confirm the relationship between wage rigidity and SCR, we run the regression by the *change* estimation for wage rigidity-SCR association with controlling for the other variables.

Table 4. The results of panel regression by using the ordered response model.

Panel A. Ordered Probit Regression

Model	Coefficient	Standard Error	*z*-Statistic	*P*-Value
ΔWR	-0.001	0.000	-1.750	0.081*
ΔGNI	0.000	0.000	0.320	0.752
ΔCA	0.000	0.000	0.160	0.870
ΔND	-0.000	0.000	-0.710	0.475
ΔINTR	-0.130	0.163	-0.800	0.426
ΔNFA	0.000	0.000	0.300	0.764
Number of Observations: 247				
Log Pseudo Likelihood: -447.97658		Pseudo R-square: 0.2387		
Wald Chi-square Statistic: 2.87		Probability > Chi-square Statistic: 0.0032		

Panel B. Ordered Logit Regression

Model	Coefficient	Standard Error	*z*-Statistic	*P*-Value
ΔWR	-0.002	0.001	-1.660	0.098*
ΔGNI	0.000	0.000	0.21	0.830
ΔCA	0.000	0.000	0.150	0.877
ΔND	-0.000	0.000	-0.970	0.334
ΔINTR	-0.253	0.304	-0.830	0.405
ΔNFA	0.000	0.000	0.260	0.792
Number of Observations: 247				
Log Pseudo Likelihood: -440.1103		Pseudo R-square: 0.1908		
Wald Chi-square Statistic: 2.70		Probability > Chi-square Statistic: 0.0030		

Notes: This table presents both ordered probit and logit regressions, with controls for the relationship between wage rigidities and SCR. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All standard errors are calculated by using the robust covariance method.

In Table 4, all the estimates for the change in the wage rigidity measure are significantly negative. The results are qualitatively similar to those of prior tests shown as Table 3. Additionally, we adopt *GDP* (replacing *sales*) as a cause of wages to measure wage rigidity and then also test both regime-switching and empirical specification for the wage rigidity-SCR link as another robustness check.

Table 5. Regime-switching regression of wage growth on GDP growth.

Regime	Dependent Variable	Independent Variable	Coefficient Estimate	z-Statistic
Rigid Slope	$\Delta wage_{it}$	Δgdp_{it}	1.067	0.462
Flexible Slope	$\Delta wage_{it}$	Δgdp_{it}	0.765***	34.820
Regime	Probability Regressor		Logistic Coefficient Estimate	z-Statistic
Flexible Slope	$I(\Delta wage_{it-1} < 0)$		-1.914**	-2.079

Notes: The first and second rows present estimates for the rigid and flexible slope parameters for the regression for $\Delta wage_{it} = \gamma_0 + \beta_m \Delta gdp_{it} + \sigma_m \varepsilon_{it}$; the third row reports the estimate for $I(\Delta wage_{it-1} < 0)$ for the regime probability under the flexible regime. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 shows the estimation result for the regime-switching model using GDP driver. The result is qualitatively similar to that of prior test using sales (presented by Table 2). Then, we run regression (22) for the wage rigidity-SCR association again.

Table 6. Results of panel regression by using the ordered response model.

Panel A. Ordered Probit Regression

Model	Coefficient	Standard Error	z-Statistic	P-Value
WR	-1.066	0.339	-3.140	0.002***
GNI	0.000	0.000	14.830	0.000***
CA	0.000	0.000	0.170	0.865
ND	-0.000	0.000	-5.880	0.000***
INTR	-0.033	0.006	-5.510	0.000***
NFA	0.000	0.000	-0.130	0.897
Number of Observations: 266				
Log Pseudo Likelihood: -539.2328		Pseudo R-square: 0.2882		
Wald Chi-square Statistic: 268.60		Probability > Chi-square Statistic: 0.0000		

Panel B. Ordered Logit Regression

Model	Coefficient	Standard Error	z-Statistic	P-Value
WR	-1.688	0.716	-2.360	0.018***
GNI	0.000	0.000	12.360	0.000***
CA	0.000	0.000	-0.080	0.940
ND	-0.002	0.001	-5.540	0.000***
INTR	-0.061	0.010	-6.180	0.000***
NFA	0.000	0.000	0.030	0.978
Number of Observations: 266				
Log Pseudo Likelihood: -537.30877		Pseudo R-square: 0.2907		
Wald Chi-square Statistic: 230.49		Probability > Chi-square Statistic: 0.0000		

Notes: This table presents both ordered probit and logit regressions, with controls for the relationship between wage rigidities and SCR. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All standard errors are calculated by using the robust covariance method.

Table 6 presents the results for the ordered probit and logit regressions using GDP-related wage rigidity measures. The results reconfirm that great wage rigidity erodes SCR.

5.3 Flows from Wage Rigidity via Cash Flow Volatility to SCR

5.3.1 Effect of Wage Rigidity on Cash Flow Volatility

As a first step toward a country's credit risk, we investigate the effect of wage rigidity on cash flow volatility. Table 7 presents the related result.

Table 7. Regression of cash flow volatility on wage rigidity and employment.

	Estimate	Standard Error	*t*-Statistic	*P*-Value
WR	0.609***	0.221	2.750	0.006
EMP	26.729	17.871	1.500	0.136
EMP * *WR*	8.553**	3.419	2.500	0.013
Adjusted *R*-square	0.058			
N	266			

Notes*:* This table presents a linear panel regression of the relationship between wage rigidity and cash flow volatility. CFV_{it} is the cash flow volatility, WR_{it} is the wage rigidities, and EMP_{it} is employment. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All standard errors are calculated by using the robust covariance method. Wage rigidity and employment are in the log scale.

We begin by running the following regression:

$$CFV_{it} = \gamma_0 + \gamma_1 WR_{it} + \gamma_2 EMP_{it} + \gamma_3 EMP_{it} * WR_{it} + \varepsilon_{it}, \tag{25}$$

where CFV_{it} is the cash flow volatility, WR_{it} is the wage rigidities, and EMP_{it} is the employment.[12] Regression (25) is motivated by (10), which is $(\partial CF/\partial z) = \{n + [c'(n)/c''(n)]\}\{1 - (\partial w/\partial z)\}$. We further envisage the relationship in (10) by considering $c(n) = e^n$ as an example of the hiring cost function. Then, the first and second derivative functions of $c(n)$ are commonly equal to e^n, and thus $c'(n)/c''(n)$ is equal to 1. As a result, (10) conforms to $(\partial CF/\partial z) = \{1 - (\partial w/\partial z)\} + n\{1 - (\partial w/\partial z)\}$, which closely relates to regression (25). In other words, CFV_{it}, WR_{it}, and EMP_{it} in regression (25) correspond to the empirical counterparts of $(\partial CF/\partial z)$, $\{1 - (\partial w/\partial z)\}$, and n, respectively. Therefore, the interaction term $EMP_{it} * WR_{it}$ in regression (25) is its empirical counterpart of $n\left\{1 - \left(\frac{\partial w}{\partial z}\right)\right\}$.

[12] Detailed descriptions of the variables used in the regression are discussed in section 3.

Regression (25) aims mainly to test for the effect of wage rigidity, WR_{it}, on cash flow volatility, CFV_{it}. Table 4 reports significant and positive estimates for wage rigidity, which imply that greater wage rigidity leads to greater cash flow fluctuation. Table 4 also shows that the estimate for the interaction term, $EMP_{it} * WR_{it}$, is positive and statistically significant. This result is consistent with the positive product term of n and $\{1-(\partial w/\partial z)\}$, $n\{1-(\partial w/\partial z)\}$, which is on the right-hand side of $(\partial CF/\partial z) = \{1-(\partial w/\partial z)\} + n\{1-(\partial w/\partial z)\}$. Note that the latter equation for $c(n) = e^n$ is a theoretical counterpart of regression (25). Finally, Table 4 shows that the estimate for the employment variable EMP_{it} is not significant. This result is consistent with the theoretical feature that the right-hand side of the equation, $(\partial CF/\partial z) = \{1-(\partial w/\partial z)\} + n\{1-(\partial w/\partial z)\}$, does not include employment, n, separately from the product term, $n\{1-(\partial w/\partial z)\}$.

5.3.2 Effect of Cash Flow Volatility on Sovereign Credit Ratings

Then, we examine the effect of cash flow volatility on SCRs by running the associated regression; we present the results thereof in Table 8.

Table 8. Impact of cash flow volatility on SCR.

Panel A. Ordered Probit Regression

Variables	Coefficient	Standard Error	z-Statistic	P-Value
$\widehat{CFV}_{it}$	-0.093	0.040	-2.320	0.020**
GNI	0.000	0.000	14.750	0.000***
CA	0.000	0.000	0.100	0.918
ND	0.000	0.000	-5.820	0.000***
INTR	-0.034	0.008	-4.180	0.000***
NFA	0.000	0.000	-0.060	0.951

Number of Observations: 266
Log Pseudo Likelihood: -529.13033 Pseudo R-square: 0.3015
Wald Chi-square Statistic: 249.11 Probability > Chi-square Statistic: 0.0000

Panel B. Ordered Logit Regression

Variables	Coefficient	Standard Error	z-Statistic	P-Value
$\widehat{CFV}_{it}$	-0.208	0.067	-3.120	0.020**
GNI	0.000	0.000	12.360	0.000***
CA	0.000	0.000	-0.150	0.878
ND	0.000	0.000	-5.380	0.000***
INTR	-0.064	0.015	-4.170	0.000***
NFA	0.000	0.000	0.080	0.934

Number of Observations: 266

Log Pseudo Likelihood: -528.66369	Pseudo R-square: 0.3021
Wald Chi-square statistic: 232.99	Probability > Chi-square Statistic: 0.0000

Notes: This table presents both ordered probit and logit panel regressions, with controls for the relationship between cash flow volatility and SCR. GNI_{it}, CA_{it}, ND_{it}, $INTR_{it}$, and NFA_{it} represent per-capita GNI, current account balance, national debt, interest rate, and net financial account, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All standard errors are calculated by using the robust covariance method.

Relevantly, we run the following regression (26) to explore the linkage between cash flow volatility and SCR. As we trace from wage rigidity to credit rating via cash flow volatility, we adopt the fitted value of CFV_{it} generated from regression (25).

$$SCR_{it} = \delta_0 + \delta_1 \widehat{CFV}_{it} + \delta_2 GNI_{it} + \delta_3 CA_{it} + \delta_4 ND_{it} + \delta_5 INTR_{it} + \varepsilon_{it}^3, \tag{26}$$

where we apply the ordered probit and logit models. $\widehat{CFV}_{it}$ is the fitted value of cash flow volatility. We consider GNI_{it}, CA_{it}, ND_{it}, $INTR_{it}$, and NFA_{it} as a group of control variables, which represent per-capita GNI, current account balance, national debt, interest rate, and net financial account, respectively. According to Table 8, all estimates for $\widehat{CFV}_{it}$ by using both ordered probit and logit regressions have significant and negative values. The negative sign implies that greater cash flow volatility induces lower SCR, consistent with the literature. Also, the results for the other control variables are qualitatively similar to those in Table 3. The estimates for the current account and net financial account regressors are not significant, while national debt and real interest rate exhibit significant and negative estimates. The estimate for per-capita GNI is significantly positive. Taken together, all the results suggest that greater wage rigidity might increase a country's credit risk through amplifying national cash flow.

6. Conclusion

This study examined the impact of wage rigidity on sovereign credit rating (SCR). The literature on SCR (e.g., Afonso et al., 2011; Bai, 2015; Favilukis and Lin, 2013) suggested that various factors of labor market rigidity negatively correlate with SCR. We contribute to the literature by directly measuring country-level wage rigidity based on our modified regime-switching specification and addressing the intervening mechanisms of cash flow volatility between wage rigidities and SCR.

Our findings can be summarized as follows. First, the results of *cross-sectional* ordered probit and logit regressions suggested a negative link between wage rigidity and SCR. Additionally, the results of probit and logit *panel* regressions consistently showed that SCR declines with the increase of wage rigidity. Finally, we performed two subtests to explore the paths among wage rigidity, cash flow volatility, and SCR. The first-phase result suggested a positive correlation between wage rigidity and cash flow volatility. By contrast, the second-phase result indicated that high cash flow volatility decreases SCR. Overall, our results suggested that a country's wage rigidity through amplified cash flow volatility negatively affects assessments of a country's credit risk.

This study provides insights into the importance of wage rigidities regarding macroeconomic consequences, thus implying that policy makers should develop an appropriate regime of labor market flexibility in order to control a country's credit risk. However, there still remain various issues regarding the channels from wage rigidities to a country's credit risk. More informative models need to be developed for individual stages. Also, downward wage rigidity might be adjusted to reduce measurement errors, considering the possible endogeneity problem.

Appendix A: ILO Wages across the 19 Countries

Table A.1. Average monthly wage in each sample country (2000–2013).

Country	Average Monthly Wage
Australia	2993.13
Brazil	568.53
Canada	2888.72
China	292.56
Germany	2827.56
Hong Kong	1573.28
India	108.13
Indonesia	110.72
Japan	3124.19
Malaysia	568.85
Netherlands	2615.68
Philippines	142.74
Poland	843.60
Russian Federation	468.29
Singapore	2523.71
South Korea	2198.69
Thailand	234.40
United Kingdom	3187.38
United States	2502.71
Average	1567.00

Notes: Values are in USD. Data source: ILO (www.ilo.org).

Table A.2. Average monthly wage across the 19 countries, by year (2000–2013)

Year	Average Monthly Wage
2000	1138.13
2001	1115.97
2002	1127.93
2003	1262.53
2004	1381.04
2005	1457.26
2006	1527.50
2007	1674.66
2008	1767.37
2009	1682.20
2010	1825.13
2011	1977.67
2012	1991.98
2013	2008.56
Average	1567.00

Notes*:* Values are in USD. Data source: ILO (www.ilo.org).

Appendix B: Simulation Results for Propositions 1 and 2

Table B.1.

$\left(\frac{\partial I}{\partial \underline{u}}\right)$	$\left(\frac{\partial L}{\partial \underline{u}}\right)$	u_B	$\underline{u}$	$\bar{u}$	x_2	I
-0.231	-0.361	0.200	-0.400	0.400	0.100	0.100
-0.212	-0.351	0.240	-0.513	0.513	0.120	0.120
-0.196	-0.343	0.280	-0.634	0.634	0.140	0.140
-0.182	-0.335	0.320	-0.763	0.763	0.160	0.160
-0.170	-0.329	0.360	-0.901	0.901	0.180	0.180
-0.159	-0.323	0.400	-1.048	1.048	0.200	0.200
-0.149	-0.318	0.440	-1.203	1.203	0.220	0.220
-0.139	-0.313	0.480	-1.368	1.368	0.240	0.240
-0.130	-0.309	0.520	-1.543	1.543	0.260	0.260
-0.122	-0.305	0.560	-1.729	1.729	0.280	0.280

Notes: We assume $\alpha = 4$, and the values of M are 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.22, 0.24, 0.26, and 0.28.

Table B.1 shows that the signs of both $\left(\frac{\partial I}{\partial \underline{u}}\right)$ and $\left(\frac{\partial L}{\partial \underline{u}}\right)$ are negative under various values of other arguments, such as u_B, $\underline{u}$, $\bar{u}$, x_2, and I. The first-order condition for the optimal investment, which is $f'(I^*) = 1 + (f(I^*) + x_2)\left[\frac{1}{\bar{u}-u_B}\right]$, implies that the optimal investment, I^*, relates to the investment return at final period (x_2), the default boundary (u_B), and the maximum cash flow shock ($\bar{u}$), the last of which is the negative value of the minimum cash flow shock, $\underline{u}$. Additionally, we denote $(B - x_0 - \overline{x_1})$ with M and assign some alternative values to it—namely, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.22, 0.24, 0.26, and 0.28. Note that the default boundary, u_B, takes positive values between their corresponding minimum and maximum cash flow shocks.

Table B.2.

$\left(\frac{\partial I}{\partial \underline{u}}\right)$	$\left(\frac{\partial L}{\partial \underline{u}}\right)$	u_B	$\underline{u}$	$\bar{u}$	x_2	I
-0.231	-0.361	0.200	-0.400	0.400	0.100	0.100
-0.202	-0.346	0.240	-0.537	0.537	0.300	0.120
-0.179	-0.335	0.280	-0.692	0.692	0.500	0.140
-0.160	-0.325	0.320	-0.866	0.866	0.700	0.160
-0.144	-0.317	0.360	-1.059	1.059	0.900	0.180
-0.130	-0.311	0.400	-1.273	1.273	1.100	0.200
-0.118	-0.305	0.440	-1.508	1.508	1.300	0.220
-0.107	-0.299	0.480	-1.766	1.766	1.500	0.240
-0.097	-0.295	0.520	-2.049	2.049	1.700	0.260
-0.088	-0.291	0.560	-2.359	2.359	1.900	0.280

Notes: We assume $\alpha = 4$, and the values of M are 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.22, 0.24, 0.26, and 0.28.

In Tables B.2 and B.3, we check for any possible change in the sign of $\left(\frac{\partial I}{\partial \underline{u}}\right)$ and $\left(\frac{\partial L}{\partial \underline{u}}\right)$ by modifying the conditions considered for Table B.1. First, we compare Table B.1 to Table B.3 by upscaling the increment of x_2 to 2 in Table B.2, while keeping all other conditions identical to those in Table B.1.

Table B.3.

$\left(\frac{\partial I}{\partial \underline{u}}\right)$	$\left(\frac{\partial L}{\partial \underline{u}}\right)$	u_B	$\underline{u}$	$\bar{u}$	x_2	I
-0.231	-0.361	0.200	-0.400	0.400	0.100	0.100
-0.243	-0.309	2.220	7.062	-7.062	0.120	2.100
-0.797	0.363	4.240	3.102	-3.102	0.140	4.100
-0.968	15.407	6.260	0.879	-0.879	0.160	6.100
-1.017	9.047	8.280	-1.125	1.125	0.180	8.100
-1.032	0.314	10.300	-3.072	3.072	0.200	10.100
-1.037	-0.529	12.320	-5.002	5.002	0.220	12.100
-1.038	-0.772	14.340	-6.928	6.928	0.240	14.100
-1.037	-0.873	16.360	-8.855	8.855	0.260	16.100
-1.035	-0.923	18.380	-10.784	10.784	0.280	18.100

Next, we compare Table B.1 to Table B.3 by upscaling the increment of I to 2 in Table B.3, while keeping all other conditions identical to those in Table B.1. Some signs of $\left(\frac{\partial L}{\partial \underline{u}}\right)$ are positive and thus inconsistent with Proposition 2; in those cases, however, all the values of the default boundary, u_B, exceed the larger of $\underline{u}$ and $\bar{u}$, and thus always cause default to the firms. In the latter situation, firms never survive at date 1, and their decision regarding long-term investment is meaningless. Therefore, we exclude those results in Table A-5 when considering the signs of $\left(\frac{\partial I}{\partial \underline{u}}\right)$ and $\left(\frac{\partial Z}{\partial \underline{u}}\right)$ and focus only on the results in Tables B.1 and B.2. As shown in Tables A.1 and A.2, both $\left(\frac{\partial I}{\partial \underline{u}}\right)$ and $\left(\frac{\partial L}{\partial \underline{u}}\right)$ take negative signs and support Propositions 1 and 2.

Appendix C: Effects of Employment

Table C.1. Effect of employment on SCR.
Panel A. Ordered Probit Regression

Variables	Coefficient	Standard Error	*z*-Statistic	*P*-Value
EMP	25.879	8.956	2.890	0.004**
GNI	0.000	0.000	12.81	0.000***
CA	-0.000	0.000	-0.230	0.821
ND	-0.000	0.000	-5.360	0.000***
INTR	-0.057	0.009	-5.950	0.000***
NFA	0.000	0.000	0.120	0.904
Number of Observations: 266				
Log Pseudo Likelihood: -533.12306		Pseudo R-square: 0.2962		
Wald Chi-square Statistic: 262.33		Probability > Chi-square Statistic: 0.0000		

Panel B. Ordered Logit Regression

Variables	Coefficient	Standard Error	*z*-Statistic	*P*-Value
EMP	24.121	8.643	2.790	0.005**
GNI	0.000	0.000	12.780	0.000***
CA	-0.000	0.000	-0.220	0.823
ND	-0.000	0.000	-5.360	0.000***
INTR	-0.058	0.009	-5.960	0.000***
NFA	0.000	0.000	0.120	0.904
Number of Observations: 266				
Log Pseudo Likelihood: -532.24166		Pseudo R-square: 0.2974		
Wald Chi-square Statistic: 220.41		Probability > Chi-square Statistic: 0.0000		

Notes*:* This table presents the results of ordered probit and logit panel regressions in relation to the association between employment and SCR. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All standard errors are calculated by using the robust covariance method.

Table C.1 shows the effect of employment on SCR by running both ordered probit and logit panel regressions. The results suggest that a greater level of employment is associated with a higher SCR.

Table C.2. Effect of employment on wage rigidity.

	Estimate	Standard Error	*t*-Statistic	*P*-Value
WR	-0.002*	0.001	-1.760	0.079
Adjusted *R*-square	0.014			
n	266			

Notes*:* This table presents the results of a linear panel regression of the relationship between wage rigidity and cash flow volatility. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. All standard errors are calculated by using robust covariances. The estimate for constant is omitted, to save space. Wage rigidity and employment are in the log scale.

Table C.2 exhibits the linkage between employment and wage rigidity. The result shows that employment levels are negatively associated with wage rigidity's level.

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Highlights

- We estimate the degree of wag rigidities by using the regime switching model.
- We relate the wage rigidity to credit risk via cash flow volatility. .
- Our simulation supports that larger cash flow volatility results in higher credit risk.
- We empirically find that greater wage rigidities raise cash volatility and worsen sovereign credit risk.