Macroeconomic Conditions, Corporate Default Risk, And The Adaptive Market Hypothesis: Principal Indicator and Early Warning Signal

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This fourth draft: June 2, 2016

Abstract

Introducing a cutting-edged technique from nature science to measure macroeconomic conditions, we investigate how macroeconomic conditions interact with corporate default risk in US industrial firms over time and how macroeconomic conditions predict corporate default risk. Based on extensive data sets on macroeconomic factors from January 1980 to December 2014, this paper measures various macroeconomic conditions in different intervals after considering structural breaks in the series. We find that corporate defaults (macroeconomic conditions) make macroeconomic conditions (corporate defaults) worse in the intervals covering savings and loans crisis in the 1980s and 1990s (covering the financial crisis of 2007-09), which is consistent with Bernanke (1993)(Bhamra et al. (2011)) 's finding. However, we determine that there is no interaction between them in the interval covering the recession occurring in March 2001. We find that their interactions between them may not be related to the certain industrial sectors as technology and communication but consumption and capital sectors. Interestingly, the phenomenon of dynamic interaction provides empirical support for the adaptive market hypothesis (AMH) in the credit market since the predictive ability of macroeconomic conditions is time-varying. Although this interaction changes over time, we find that macroeconomic conditions have predicting power of explaining corporate defaults that are not triggered by macroeconomic shocks. These results provide empirical support for recent theories that macroeconomic conditions make corporate defaults worse, and they also provide an implication of building an early-earning system in order to capture future collapse in the credit market, even though the predicting power is limited to the defaults caused by macroeconomic shock.

JEL classification: G01, G14, G17, G33, E32.

Keywords: Corporate default risk; default behaviour; macro indicator; critical transitions; macroeconomic conditions; AMH;

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1. Introduction

This paper aims to introduce a cutting-edged technique for measuring macroeconomic conditions from nature science by using hundreds of macroeconomic factors covering the January1980-December 2014 period. Then we investigate how macroeconomic conditions interact with corporate default risk in US industrial firms over time and determine how macroeconomic conditions have predictive content on corporate default risk.

Our motivation for doing this work is sixfold. First, although default crises have been the focus of many studies, prior studies mainly focus on default crises in the listed firms. The primary reason for this may simply be that the firm-specific information in the non-listed firms is not available to researchers. For example, Merton model and its extensions is only limited to listed firms since these models are based on equity-price information. However, Jacobson et al. (2013) argue that the privately held firms are typically responsible for over half of GDP in developed economies. Additionally, this study only focuses on the relationship between macroeconomic conditions and corporate defaults. Then, both two types of firms should be considered simultaneously, which can reflect the big picture of corporate defaults in the industrial economic sector.

Second, this study is to initially introduce a cutting-edged technique from nature science, which is to use generic indicators to indicate the potential for critical transitions in a complex system or capture the cascade effects in the system[2]. Then we can use this approach to capture such transitions or cascade effects in the macroeconomic system thereby measuring macroeconomic conditions. According to Scheffer et al. (2012), prior studies construct various empirical indicators for capturing critircal transitions in the complex system and detecting their tipping points. This technique has already been widely used in ecology and climate science. Now, there are quite a few such as epilepsy, medicine, engineering that engaged on this work, particularly in social science. Recently, it has been introduced in Finance, such as Gorban et al. (2010) use this technique to reflect the trend of FTSE 100 and they also find that the correlations among stock returns increase significantly in crisis. However, this approach has not been introduced in analyzing economic system.

Helbing (2013) explains that economic theories such as equilibrium paradigm regard economies as the systems that tend to evolve towards an equilibrium state. Additionally, they have not recognized the interactions between system elements that can trigger amplifying cascade effects even if all components relax to their equilibrium state. However, he claims that even in the current economy, there are cascade effects since because of the spread of innovation and products. For example, central bank as the policymaker may increase interest rates thereby curbing overheated economy, which

[2] Specifically, Scheffer et al. (2012) explain that “Sharp regime shifts that punctuate the usual fluctuations around trends in ecosystems or societies may often be simply the result of an unpredictable external shock. However, another possibility is that such a shift represents a so-called critical transition. The likelihood of such transitions may gradually increase as a system approaches a “tipping point” [i.e., a catastrophic bifurcation], where a minor trigger can invoke a self-propagating shift to a contrasting state.” We can conclude that critical transitions show the process of changes in the system. Meanwhile, the accumulation of such transitions lead to tipping points, which may indicate high probablity of unwanted collaphse in the system, or opportunities or positive change.

They state that in a complex system the occurrence of critical transitions imply there are interactions among the system components. The phenomenon of interactions results in cascade effects or domino effects. Specifically, if the interactions among system components become strong, the behavior of these components may greatly vary or influence the functionality or operation of other components. Helbing (2013) clarifies that “One event can trigger further events, thereby creating amplification and cascade effects, which implies a large vulnerability to perturbations, variations or random failures. Cascade effects come along with highly correlated transitions of many system components or variables from a stable to an unstable state, thereby driving the system out of equilibrium.”

Scheffer et al. (2012) conclude that different classes of generic observations are able to be used to indicate the potential for critical transitions in the complex system, such as correlation among system components and their variance. They also argue that tipping points that result from such transitions may provide an early warning signal for potential crisis even before obvious symptoms of crisis appear.

increase the cost of capital. The number of loans decreases rapidly and the banks slash the credit to the public. Then the firm faces a higher operation cost and cost of financing. A large number of employees are laid off and the salaries for the employees reduce, which can be reflected by the macro factors such as unemployment ratios, working hours, and initial claims etc. Production volume decreases and inventory increases, which further makes corporates worse and depresses economy again. Consequently, poor macroeconomic conditions spark the crisis in the economy and prick the bubble in any markets such as real estate market and equity market. In this context, we construct the generic indicators titled "macro indicators" to capture critical transitions in the economic system thereby measuring changes in macroeconomic conditions.

Third, the prediction of default risk has been concerned by many studies since the first bankruptcy model was created by Altman (1968); they have a common weakness of applying theories for well-behaved systems that are not well behaved[3]. Specifically, these models often assume that financial (credit) market is stable and past events can give the sign for the unforeseeable events in the future; that is, these models particularly reduced form models are initially trained by the historical data and then use estimated consistent parameters to predict what happens in the future. In fact, Bernanke (1993) argues that financial market such as credit market is dynamic rather than stable. Andrew Crockett, as a former general manager in the Bank for International Settlements wrote the foreword in the Ramaswamy (2004)'s book. He declares that "we must be particularly mindful of the possibility that the future will be different from the past". Bernanke (1993) also argues that the predictive power for the predictors should reflect the market's perception of default risk. It is suggested that when the market's perception represented by economic environemnet to default risk changes, the predictor should change as well. In 2001, the Conference Board published a book called *Business Cycle Indicators Handbook* argues that the U.S. economy is continually evolving and is far too complex to be summarized by one economic series and also some factors are only useful in certain set of conditions, others in a different set. However, early studies about how macroeconomic conditions predict corporate default risk mainly use several macro factors such as GDP, SP500, 3-month T-bill rates and they find that they have strong predicting power on default risk (Duffie et al., 2007, Das et al., 2007, Couderc et al., 2008, Duffie et al., 2009). Then, these macro factors may not better capture entire macroeconomic conditions and even may not be able to capture the future changes in macroeconomic conditions. In contrast, generic indicators are able to avoid the problems mentioned above, and it can even capture any macroeconomic shocks in the economic systems by allowing for numerous macro factors simultaneously. Another advantage of using generic indicators is that these approaches can be used in any particular system even if we fail to understand how specific mechanisms drive these systems (Scheffer et al., 2012)[4]. Therefore, using generic indicators to measuring macroeconomic conditions

[3] The prior literature shows that the major models are generally divided into two categories: structural models and reduced form models, respectively (McNeil et al., 2010). Key theoretical study in the structural models includes Black and Scholes (1973), Merton (1974), Black and Cox (1976), Fischer et al. (1989), Leland (1994), Longstaff and Schwartz (1995), Leland and Toft (1996), Collin-Dufresne et al. (2001), Goldstein et al. (2001), and Bharath and Shumway (2008). For core theatrical work about the reduced form models, they are Ohlson (1980) and Zmijewski (1984), Jarrow and Turnbull (1992), Shumway (2001), Duffie et al. (2007), Das et al. (2007), Campbell et al. (2008), Duffie et al. (2009), Giesecke et al. (2011), Koopman et al. (2011), and Azizpour et al. (2014). In addition, the techniques used in the industrial world have same weakness. Sornette and Woodard (2010) provide the evidence of the quantitative statistical models based on Monte Carlo simulations and used by principal credit rating agencies (CRAs) including Moody's, Fitch and Standard & Poors fail to predict the probabilities of default for CDO or MBS. Since these models use historical default rates derived from 1990 to 2000 with low mortgage default rates and home prices are increasing to do estimation. Therefore, they cannot correctly capture the high defaults of mortgages due to a general housing bust. They also show the other two possible reasons that for the complexity of some new financial instruments, CRAs also fail to correctly calculate their default since they do not have historical return data for those instruments on which to base their risk assessments. Additionally, CRAs may deliberately inflate their ratings to attract the issuers thereby increasing their consulting fees.

[4] The generic features mean the cascade effects in any complex systems and we can use correlation and variance to measure the critical transitions in these systems in order to determine the unwanted collapses in the future.

not only extends the understanding of how macroeconomic conditions evolve, but also sheds new light on how to construct a new mechanism for predicting corporate defaults in unstable credit market.

Fourth, while there have been theoretical debates whether dynamic of macroeconomic conditions either results from corporate defaults or results in corporate defaults, relatively little attention has been given to empirical investigation about whether they interact with each other. Specifically, for the first scenario, corporate defaults have a powerful effect on the economy, which leads to the economy slowdown and macroeconomic conditions become worse. Gertler (1988) determines that credit market conditions play a central role in the propagation of cyclical fluctuations. Bernanke et al. (1999) further explain that deteriorated credit market conditions reflected by sharp increases in insolvencies and bankruptcies, rising real debt burdens, collapsing asset prices, and bank failures have significant impact on the economy, and it can slow down economic activity. For the counterparty of first scenario, macroeconomic conditions can affect corporate defaults; that is, weakened macroeconomic conditions result in corporate defaults. Hackbarth et al. (2006) find that previous literature pays little attention on the effects of macroeconomic conditions on credit risk and capital structure choices, and they identify that macroeconomic conditions should have a large influence on credit risk and firms' financing decisions. Chen (2010) builds a dynamic capital structure model to verify how firms finance during the business cycle and he also determines that macroeconomic conditions affect firm decisions, which reversely influence the riskiness of the firms. This paper hopes to deeply investigate the interaction between macroeconomic conditions and corporate defaults from empirical perspective.

Fifth, an increasing number of studies have been interested in examining Adaptive Market Hypothesis (AMH) [important examples include Neely et al. (2009), Smith (2012), Urquhart and McGroarty (2014)]; majority studies pay attention to equity market and exchange market and no studies yet concentrate on the credit market in the literature. This phenomenon may be caused by two possible reasons as follows. One is that in order to reconcile the efficient Market Hypothesis (EMH) and behaviour finance, Lo (2004) proposes AMH based on equity market, and then following empirical studies mostly focus on stock market; another is that data in both exchange and stock market can be easily accessed for examination. The credit market, however, has been a major part in the financial market, which has similar features as equity markets. Specifically, in EMH, the market is efficient since all information should be reflected in stock prices; however, AMH implies that market efficiency varies over time and both the EMH and market inefficiencies co-exist in an intellectually consistent manner. Lo (2004) claims that based on evolutionary principals, the degree of market efficiency results from the biological perspective, such as the number of competitors in the market, the magnitude of profit opportunities available, and the adaptability of the market participants. In fact, this is also the same case in the credit market. Bernanke (1993) argues that the credit market is filled with imperfect and asymmetric information, which makes market inefficiency. He also argues that if credit market is efficient, "price" representing the interest rate or expected yield, should reflect all information. This is consistent with the main idea in EMH. He determines that two elements including existence of banks or other financial intermediaries and the structure of financial contracts lead to the degree of market efficiency. For example, the number of intermediaries such as banks, pension funds, and life insurance firms etc., has expertise on collecting, evaluating, and monitoring borrowers' information, which can overcome the market inefficiencies. Meanwhile, the form of the financial contract between the lender and the borrower may have significant effects on the borrower's incentives to honestly uncover information and/or to make business decisions that cater to the creditor's interest. The imperfect information can be reflected by the circumstance of adverse selection, risk concentration, and moral hazard in the credit market, and these circumstances also exist in the equity market (Duffie and

Singleton, 2012)[5]. It is clear that the fundamental of market inefficiency is the same for both credit and equity market.

AMH states that individuals act in their own self-interest, and they can make mistakes. They learn and adapt from these mistakes and the competition derives adaption and innovation, which leads to a number of valuable implications. One of them is that investment strategies can be successful or unsuccessful, which depends on certain environments. Compared with EMH, AMH indicates that these strategies may decrease for a time and then return to profitability, when environmental conditions become more conducive to such strategies. This leads to another key implication, which is that market efficiency is not an all-or-nothing condition, but varies continuously over time and across markets. Lo (2004) argues that convergence to market efficiency is neither guaranteed nor likely to occur. In the credit market, such investment strategies can be macroeconomic conditions. Corporate default probabilities as a proxy for default risk is used to reflect the credit market conditions. Following AMH, the predictive power of macroeconomic condition may decline or at least may be limited in certain environment for corporate default probabilities, which is almost consistent with the fourth motivation mentioned above. We hope to examine whether AMH is reasonable in the credit market in terms of determining the time-varying predictability of macroeconomic conditions on corporate default risk.

Sixth, using the macro indicators, we hope to be able to provide a mechanism for verifying recent theoretical finding which is that dynamic of macroeconomic conditions can impact default risk trigged by macroeconomic shocks and provide a framework of how to predict default risk based on macro factors by building an early-earning system. This is because firm defaults can be caused by various factors except changes of economic environment (business cycle), such as poor corporate governance, business failures, and firm scandals etc. Following prior studies, defaults clustering are generated by macroeconomic shocks. It can be expected that excluding the defaults that are not caused by the macroeconomic shocks, there may be no default clustering. For these defaults, they are likely small default events. That is, these small default events are the outliers or noisy for predicting default clustering by macro indicators.

For this theoretical finding, Shleifer and Vishny (1992) explain that the debt capacity of firm is associated with the current economic conditions and firms typically are able to obtain more financing sources in the boom period, even assuming a constant loss given default. That is, firms are easy to avoid financial unhealthy problem in boom compared with in bust. Then firms tend to default in the bad economic environment. Hackbarth et al. (2006) find that previous literature pays little attention on the effects of macroeconomic conditions on credit risk and capital structure choices and they identify

[5] Specifically, the case of "flight to quality" may happen because of adverse selection (Bernanke et al., 1994). For example, in reality, the business lenders as banks cannot know more than the borrowers in terms of their default risk. The bank makes profit in the tight period to attempt to compensate for default risk by considering whether the borrowers can provide high quality of collaterals. However, the collaterals provided by borrowers may not correspond to the real value shown in the contract. Then bank in this situation allows the borrowers to select the sizes of their own loans without restriction.

For the case of risk concentration, the default cluster occurring in the credit market can be understood. Specifically, broker-dealers in the banks and Over-The-Counter (OTC) measure and limit the default risk, relying on two standards including individual counterparties and industry groups, geographic regions and sometimes other classifications (Duffie and Singleton, 2012). Assuming that various banks have different knowledges about the credit risk in the real estate industry. If some banks set a naïve rate depending on their own best estimates of the expected rate of losses owing to default compared with the other banks setting a high rate, many borrowers prefer to choose the banks offering attractive rates even if these banks have no private information about their own credit quality. In this context, a large amount of loans from these banks flow to the unqualified borrowers, which suggests that these banks will therefore suffer an expected loss on their real estate loans. Then default cluster can happen among banking industry if there is a high default happening in the borrowers in the recession period.

Moral hazard also exists in the credit market. Duffie and Singleton (2012) declare that since the small loans are less risky than large loans, other things being equal, the borrowers borrowing large loans have strong motivation of undertaking riskier behavior than the borrowers borrowing small loans.

that macroeconomic conditions should have a large influence on credit risk and firms' financing decisions. They figure out that if the firms determine optimal leverage by balancing the tax benefit of debt and bankruptcy costs, then both the cost and benefit of debt should rely on macroeconomic conditions. Since the debt's tax benefit is dependence of the level of cash flows, the amount of cash flow depends on the states of economy including expansion and contraction. Additionally, both the probability of default and the loss given default influenced by the state of the economy result in the expected bankruptcy costs. Then it can be suggested that firms are easy to default in the bust period since the less cash flow may lead to higher tax cost and non-benefit of debt. Chen (2010) builds a dynamic capital structure model to verify how firms finance during the business cycle and they finally determine that macroeconomic conditions affect firm decisions, which reversely influence the riskiness of the firms. More importantly, this model provides a rational mechanism for "credit contagion" and market timing of debt issuance. He find that "these clustered defaults are due to a sudden deterioration of macroeconomic conditions that causes firms' default boundaries to jump up, so that those firms with cash flows below the new default boundaries will default simultaneously."[6] He also uses the timing of issuing the debt to explain this clustering phenomenon. Generally speaking, the monthly rates of issuing debt are procyclical with business cycle, and they often reach the peach level when the economy switches from a bad state to a good state, suggesting that a large amount of firms issue debt simultaneously. For example, in the booming period, firms tend to issue more debt since the interest become lower, and credit spreads (borrowing costs) decrease at the same time; in contrast, they tend to decrease debt issuance. In this context, many firms have a higher tendency of going to default in the bust period.

From empirical studies such as Chava and Jarrow (2004), Das et al. (2007), Duffie et al. (2007), this clustering phenomenon can be interpreted as firms that are exposed to common or correlated risk factors such as interest rates, stock returns, and GDP growth. The comovement among these macro factors can lead to associated changes in the conditional default rates of the firms. Fundamentally, strong economic growth decreases the likelihood of default across the board. Several studies also identify that there is a time lag between economic recession and default clustering and high defaults seemingly follow the occurrence of economic recession (Koopman et al., 2009, Koopman and Lucas, 2005, Couderc et al., 2008). Therefore, clustered defaults are highly correlated with macroeconomic conditions.

To provide construction of macro indicators for measuring macroeconomic conditions, we begin with classification of macro factors for measuring macroeconomic environment. In the economic literature on business cycle, scholars handle groups of series to represent a general type of activity, which is able to define broadly economic process. Shiskin and Moore (1967) argue that the economic process can explain business cycle phenomena. In this context, this paper classify 114 macro factors into 5 different groups, which are the group of all the macro factors, the group of factors from 6 economic groups, the group of leading factors, the group of procyclical factors, and the group of effective factors extracted by least absolute shrinkage and selection operator (Lasso) developed by Tibshirani (1996). The first two groups of factors are used to reflect comparatively complete macroeconomic conditions, which are titled augmented macroeconomic conditions and generalized macroeconomic conditions, respectively. The rest of them are used to capture incomplete/specific macroeconomic conditions. Then we construct five macro indicators by five groups of series.

We find that these macro indicators change over time within business cycle, which almost move between expansion and contraction. When there is no NBER recession in the economy, macro indicators tend to decrease and fluctuate in the low level; when recession occurs, the macro factors

[6] According to Leland (2004), A "default boundary" can be defined as a level of asset value which may vary with the shit of time. If the value of a firm' asset is below to this level, then this firm will default on its debt.

rapidly increase then. Therefore, it can be concluded that the if there are higher correlations among macro factors, then macroeconomic conditions become worse, implying that the probability of economic recession occurring goes up; otherwise, the economic conditions becomes better with a lower probability of occurrence of economic recessions. Meanwhile, we also find that when the indicators reach a high level, the default risk also tend to be quite high, suggesting that there is a relationship between various macroeconomic conditions and corporate defaults. Both two indicators constructed by all the factors and factors in 6 economic groups have similar trend, indicating that groups of series in 6 economic groups are able to almost reflect the relatively entire picture of macroeconomic environment. The other two indicators defined by narrow groups of series have different trends in certain periods, which only reflect the incomplete macroeconomic conditions. Although the indicator constructed by effective factors only covers 29 factors, the overall trend of corporate defaults is similar as the trend of dynamic of this indicator.

Next, we initially focus on two indicators constructed by all the factors and factors in the 6 economic groups since they are able to reflect considerably broad macroeconomic conditions. After doing causality analysis, we confirm that there is a dynamic interaction between macroeconomic conditions and corporate default over time in the US industrial films. In the whole sample, corporate default risk has long-run relationship with macroeconomic conditions and it can impact macroeconomic environment. However, in the short sample, this is not the case. Corporate default risk is able to have influence on macroeconomic conditions before November 1998. These results strongly support theoretical literature about how corporate defaults can explain changes of macroeconomy (Gertler, 1988, Bernanke, 1993, Bernanke et al., 1994, Bernanke et al., 1999). This finding gets the support from Bernanke (1993) who finds that the savings and loans crisis occurred in the 1980s and 1990s provides evidence of how corporate defaults make economy worse.

Then after November 1998, dynamic of macroeconomic conditions reversely affect corporate defaults except the special interval covering the recession occurring in March 2001. These results get the support for theoretical literature about macroeconomic environment that can impact default risk (Hackbarth et al., 2006, Chen, 2010). This finding is also consistent with the study done by Bhamra et al. (2011) who argue that 2007-2008 financial crisis shows how the changes of macroeconomic environment has a severe impact on corporate defaults.

However, there is no interaction between macroeconomic conditions and corporate defaults in the recession from March 2001 to November 2001, which has not been discussed in the previous literatures. In fact, previous studies indirectly provide the evidence of explaining this phenomenon. The primary reason is that this recession has unique features compared with the other recession periods. Following normal procedure of occurrence of recession, numerous economic factors related to aggregate demand, output, and employment tend to rapidly move (Kliesen, 2003). In fact, in this period, the economy has experienced a different process since these economic factors do not behave in similar way and even overall productivity growth still remained strong during this recession period. We also find that the interaction between corporate defaults and macroeconomic conditions may depend on the specific industrial sector. In 2001, the defaults among technology firms may not provide any link between two items but capital intensive and consumer industries. This is the matter of occurrence of recession in March 2001. Stock and Watson (2003) explain that this recession is caused by the firms that cut back on expenditures in the information technology (IT bubble) rather than shopping mall and corridors of the Federal Reserve Bank. That is, the problem is not due to economic structure but specific industry. Then the influences of corporate defaults have a minor effect on whole default risk in industrial firms.

If we use the other two indicators representing incomplete macroeconomic conditions, we find that the causal relationships between incomplete macroeconomic environment and corporate defaults are not clear since more intervals have no causal relationship between them. This result corresponds to our intuition since they cannot represent entire macroeconomic conditions even the generalized level. We also find that incomplete macroeconomic conditions have better performance of explaining corporate defaults than macroeconomic conditions in certain intervals, implying that these indicators may be used as supplement tools for measuring future corporate defaults.

Particularly, compared with other macroeconomic conditions, specific macroeconomic conditions represented by the indicator constructed by effective factors tend to have strong Granger-cause corporate defaults even in the long-run period except in the short intervals. It is implied that specific macroeconomic conditions may have more predicting power than the incomplete or relatively comprehensive macroeconomic conditions. This result also indicate that these 29 factors are able to reflect the perception of default risk, which supports theoretical study done by Bernanke (1993).

Taken together, these results provide strong evidence of adaptive market hypothesis (AMH) proposed by Lo (2004) that is reasonable in the credit market. Specifically, corporate default risk reflects the risk preferences or default attitudes from market participants. According to Hackbarth et al. (2006), once debt has been issued, equity holders hold the right to decide whether they are going to default or not in response of changes of economic conditions. In addition, macroeconomic conditions have power to influence the cash flow, which further affect tax benefit and bankruptcy costs. Then they lead to the financing and default decisions for the decision makers in the firm (Hackbarth et al., 2006, Chen, 2010). Our results show that the behaviors of corporate defaults either interact with the changes of macroeconomic conditions or do not interact with the changes of macroeconomy, which reflects the dynamic between market participants' behavior and changes of market conditions. That is, the predictability of macroeconomic conditions is not constant but varies over time. This finding provides empirical evidence for AMH since investment strategies can only be successful in certain environments and they are unsuccessful once that environments shift. Thus we confirm that AMH is reasonable in credit market.

Based on the finding of macroeconomic conditions that Granger-cause default risk in certain intervals, we further verify theoretical finding of whether macroeconomic conditions that can predict default risk after removing small default events and investigate how much power macroeconomic conditions consisting of each macro indicator and NBER economic recessions have in terms of explaining corporate default risk. For the number of small default events, this study uses 5 as a filtering standard. There are three motivations. First, scatter plot shows a rough linear relationship between default probabilities and each indicator when the months having less than 5 default events. Second, the mean of the number of defaulters in Table 3 is 5.445 and the value of 25% of total default sample is 2. Then removing the months with less than 5 defaults can allow for keeping the small default events removed from total sample. Third, based on model performance and predicting power of each indicator, 5 is a also turning point. If the other values are used, then predicting power decreases and fitted model cannot satisfy model assumptions. Therefore, this study uses 5 as the boundary for filtering small defaults; that is, this study only removes the months with less than 5 defaulters. Three hypotheses are proposed for verification and investigation, which are listed below:

1. Hypothesis 1: Can changes of macro indicators explain corporate default risk?
2. Hypothesis 2: Can NBER recessions explain corporate default risk?
3. Hypothesis 3: Is there an additive effect between macro indicators and NBER recession on predicting corporate default risk?

We find that the indicator constructed by effective factors has the best predicting performance, which is followed by the indicator constructed by all the factors, factors from 6 economic groups, leading factors, and procyclical factors. This result corresponds to the finding of using causality test. Meanwhile, this result further determines that if more factors are considered in constructing macro indicator, we are able to capture more transitions in the macroeconomic system. However, adjusted R-squared are from 49% to 30% for using these indicators with NBER recessions. Then we confirm that the predicting power by using macroeconomic conditions is limited to some extents. These results support theoretical finding of macroeconomic conditions that can make corporate defaults worse.

In particular, after lagging each indicator and NBER recession by 3 months, only the indicator constructed by leading factor improves the performance of predicting corporate default risk, which is consistent with the intuition. Since leading factors normally move more at least one month earlier than the other factors, then lagging this indicator may better predict corporate defaults. However, the order of the predicting power of each indicator is still same as without considering lag on series except the indicator constructed by leading factors. These results further prove that using more macro factors to build indicator is able to capture critical transitions in the macroeconomic system thereby predicting potential corporate defaults. Meanwhile, they also provide an implication of building an early-warning system to predict corporate defaults based on macro indicators even though the explaining power for the default risk is limited.

The remainder of this paper is organized as follows. Section 2 describes the data set used and explains how it is constructed. Section 3 provides the empirical results, which is followed by Section 4 discussions. The final part is conclusion.

2. The data

This study focuses on the monthly corporate defaults in the industrial economic sector in the US industrial firms. The primary reason of selecting industrial firms is that the other economic sectors such as media, financial sectors, gas and electric utilities, as the return on equity, revenues, and thus the risk of the default, are strongly influenced by regulators (Eom et al., 2004). Economists consider that a strong industrial sector is a sign of well-functioning economy with a high GDP and high quality of life. That is, the performance of industrial sector depends on macroeconomic conditions thereby avoiding the influence from the government interventions. Two main databases including corporate default database and macroeconomic factors database are constructed for this paper.

2.1 Corporate Default Database

Corporate default database draws elements from Moody's Default Recovery Database (DRD). DRD provides rating transition and default history for all rated US industrial firms, which are used for calculating monthly default probabilities. The US rated firms classified as "Industrial" group in DRD are selected. The method of measuring default risk is based on issuer-weighted default probabilities (IDPs), which counts the number of monthly defaults over the rated firms in the beginning of each month. For the time span of defaults information, although Moody's started to record the default in 1898, the quality of default records is not reliable from 1898 to 1980. Then the time span is from January 1980 to December 2014.

Following previous studies such as, Davydenko (2012), Lando and Nielsen (2010), Duffie et al. (2009), Duffie et al. (2007), this study cleans defaults in order to remove the dependent default events in Moody's default database. Specifically, we first remove the influence of family structures, and the parent's consolidated financial information is used to study the default decision for the whole group of bond issuers. In addition, if a firm consecutively defaults more than a time within two years, all these multiple default events are counted as a default event and the first default date is regarded as the default date. Then, the redundant default events can be handled. This leaves us with a total of 10368 firms comprising 1842 defaults, and all the firms are both listed firms and privately held firms.

Figure 1 shows the dynamic change of time series of total defaults, total exposures, and IDPs in the US industrial firms from January 1980 to December 2014. We can find that default clustering around the recession yeas of 1990, 2001, and the financial crisis of 2007-2009 in the graph of total defaults and exposures is very clear.

2.2 Macroeconomic Database

A second database is constructed from Federal Reserve Economic Database (FRED), which contains 114 macroeconomic factors in Table 1. All variables except exchange rates, interest rates, and industrial material price index are seasonally adjusted and they are all transformed to growth rate except four yields spread ratios including T10YFF, SPREAD.GS, SPREAD.MOODY.1, and SPREAD.MOODY.2. According to the understandings of macroeconomic conditions, these macro factors are classified into 5 groups. Then this study is to use 5 groups of factors to construct different macro indicators for measuring various macroeconomic conditions. These macroeconomic conditions can be divided into four categories in Table 2. The detail descriptions are shown below.

2.2.1 Classifications of macro factors

a. All the factors

The first indicator is constructed by all the macro factors in order to reflect relatively complete macroeconomic conditions. The reason of choosing all the factors is that future event is unpredictable; that is, it is not available to predict which groups of elements in the macroeconomic environment can lead to the comovement of the other factors. This idea is supported by theoretical studies. Specifically, broad category can provide protection against significant changes in cyclical behaviour that may result from such factors as technological developments, changing consumer tastes, or the rapid growth of decline of single products or industries (Shiskin and Moore, 1967). These broad economic factors can continuously capture the potential changes in the business cycle, even though some factors that performed well in the past deteriorate in this present. In addition, scholars in the economic area still cannot find a better solution to find an effective of indicators from numerous macro factors to do future predictions of macroeconomic conditions since prior studies identify that the environment is always evolving over time and the current group of factors may only mimic dynamic change of macroeconomic conditions in the specific interval (Moore, 1961, Shiskin and Moore, 1967, Zarnowitz, 1992). Scheffer et al. (2012) figure out that "the methods for detection of incipient transitions from time series tend to require long, high-resolution data." That is, if more factors are collected for constructing macro indicator, it may capture any transitions caused by the increase of correlations from the factors that have not been considered as the trustworthy factors thereby raising the ability of capturing unpredictable changes in the macroeconomic conditions. Due to the issue of availability of macro factors used in this study, then we cannot collect and use all the macro factors from FRED. Then we can only capture relatively complete macroeconomic conditions, and this paper call it as augmented macroeconomic conditions.

b. Factors in 6 economic groups

The second indicator is constructed by 106 factors in 6 economic groups in Table 1, for example, employment and unemployment; production, income, consumption, and trade; fixed capital investment; inventories and inventory investment; prices, costs, and profits; money and credit. Shiskin and Moore (1967) discusses the issue of whether grouping the factors based on economic processes is meaningful in practice and he determines that "under the criterion of economic significance, it would seem best to evaluate groups of series representing a general type of activity, because theories which purport to explain business cycle phenomenon do not ordinarily refer to particular indicators, but rather to generalized economic processes." He proposes a solution of grouping macro indicators thereby generalizing the strategic processes in the business cycles and all the macro factors are classified into 9 types of economic groups. Excluding the 6 economic groups mentioned early, the other three economic groups are (a) foreign trade and payments, (b) federal government activities, and (c) economic activity in other countries.

He emphasizes that the first two groups are measures of aggregate economic activity and are used to show the broad movements of the business cycle and to determine the dates when there is an economic expansion and contraction starting or ending. He further declares that the next four from fixed capital investment to money and credit with the first two groups can also mirror the business cycle with a causal role in the cyclical process. The last three groups do not contribute to the cyclical fluctuations in U.S.; however, they significantly impact their pattern, amplitude, and duration. Then this study selects majority of the macro factors from the group 1 to group 6. It can be seen that these factors may show generalized macroeconomic conditions.

c. Leading factors

This indicator is constructed by using 42 leading factors in Table 1. Leading factors tend to move direction before the business cycle occurs and the timing comparisons between the cyclical turn in these economic forwarding factors and business cycle turn is one months or more, such as, new orders, housing starts, and consumer sentiment. Many practitioners and scholars use leading factors to predict the future perspective for a specific country or global economy. Compared with other two cyclical indicators including lagging and coincident factors, it can be concluded that leading factors may provide more predication information than the other two types of factors since the interaction among them may occur earlier than the interaction among coincident factors or lagging factors. We can expect that the macro indicator constructed by the group of leading factors may perform well than the other macro factors built by using lagging or coincident factors, respectively[7]. Since these factors can only deliver limited information, this indicator is used for measuring incomplete macroeconomic conditions.

d. Procyclical factors

The fourth macro indicator is constructed by procyclical factors in Table 1. According to the relation between business cycle and each economic factor, this study split them into two parts. One part contains 86 procyclical indicators; another covers 28 countercyclical indicators. Likewise, depending on the relation between each indicator and default risk, we further classify them into two groups including positive correlation and negative correlation. In fact, the results of this classification is opposite with the results in the former category by the standard based on relation with business cycle. When the economy is entering into an expansion, the business activities are very active and firms tend to have more profits with good financial conditions suggesting that default risk is quite lower. When the economy is going to negative direction, both demand and supply are quite weak and firms highly tend to face financial distress indicating that default risk is quite high[8]. Therefore, the macro factor classified as procyclical factors means that this factor has a negative influence on default risk; otherwise, it has positive impact on default risk. This method can keep the macro factors which only have negatively relationship with default risk in order to control the calculation of correlation among these factors. It should be noted that the number of countercyclical factors is quite small and the performance is also very poor in terms of explaining default risk. Therefore, this study only concerns the indicator constructed by procyclical factors, which is able to pic incomplete macroeconomic conditions.

e. Effective factors extracted by Lasso

We also uses Lasso to extract 29 effective factors for explaining default probabilities in the industrial firms. It is intuitive that the set of effective factors may outperform the other factors since these factors contains highly predictive information in explaining the past default events. That is, these factors can pic the default history from January 1980 to December 2014[9]. Therefore, the indicator constructed by

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[7] In practice, we constructed macro indicators based on either lagging or coincident factors and found that the correlation between their macro indicators and IDP are quite lower compared with macro indicator constructed by using leading factors. Then we do not use the lagging and coincident factors.

[8] In bull market, firms normally have higher profits since there is a large amount of demand. Moreover, it is easy for them to financing from the financial market thereby the illiquidity problem can be handled easily during this period. As a result, the default risk is quite small. In the bear market, demand slashes and goods price is quite lower. The firms face smaller demand and higher operation costs. The credits from the banking sectors become tightened and then the firms may not obtain financing sources from the financial market especially for the small-medium firms (SMEs) to reduce their inventories or handle illiquidity problem in the balance sheet. In this context, the default risk is quite higher.

[9] All the variables for modeling IDPs by Lasso are the growth rate except 4 spread ratios. In order to obtain appropriate model estimation, 6 different sizes of training samples such as 65%, 70%, 75%, 80%, 85%, and 90% are used for estimating Lasso and each method leads to the corresponding results. The standard of choosing the results depends on whether all these sets of results are similar. If Lasso can give us similar results even using

effective factors can show specific macroeconomic conditions for corporate defaults in the past 35 years.

2.2.2 Methods of construction of macro indicator

As discussed early, several classes of generic observations including correlation and variance can be used to indicate the potential for critical transitions in the complex system. Following suggestion from Scheffer et al. (2012), this study uses the correlation to construct the indicator, then we apply the method used by Gorban et al. (2010) for collecting correlation among macro factors. Specifically, the indictor is based on the Pearson correlation coefficient (r), and then we collect the these correlation information by using an approach called L_p norm

$$\|r\|_p = \left(\sum_{j>k} |r_{jk}|^p\right)^{\frac{1}{p}}, \tag{1}$$

where r_{jk} ($j > k$) is actually the Pearson's r beween two variables, which is equal to:

$$r_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})}}, \tag{2}$$

where X and Y represent two variables. Specifically, we have one dataset $\{X_1,, \ldots, X_n\}$ containing n values and another dataset containing n values. $\mathrm{cov}(X,Y)$ is the covariance between X and Y. $\sigma_X\sigma_Y$ is the square root of the products of the sums of squares for each attribute X and Y. $\bar{X}$ and $\bar{Y}$ are the mean value of sample X and Y. $r_{X,Y}$ is the correlation coefficient between X and Y (Nolan and Heinzen, 2011). Then we have $n(n-1)/2$ correlation coefficients between various variable, r_{jk}. It should be noted that these values are loacted non-diagnoal part of the correlation matrix.

If the strong correlations among variables is the major concern, then we can delete terms with values below threshold, $\alpha < 0.5$, from the sum $G_{p,\alpha}$

$$G_{p,\alpha} = \left(\sum_{j>k, |r_{jk}|>\alpha} |r_{jk}|^p\right)^{\frac{1}{p}}. \tag{3}$$

The quantity $G_{p,\alpha}$ is a p-weight of the G-correlaiton graph The vertices of this graph correspond to variables, and these vertices are connected by the edges, if the absolute value of the correspondent sample correaltion coefficient exceeds α: $|r_{jk}| > \alpha$. In order to concern the dynamic change of components of matrix, we calibrate the equation (3) and then the indcator is as follows:

$$\text{Indicator} = \frac{G_{p,\alpha}}{N}, \tag{4}$$

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different training samples, then the results obtained by Lasso are reliable. Then there are 6 sets of effective factors for explaining IDPs based on 6 different training sample sizes. Basically, the results tend to be stable and they are almost similar after using training sample sizes such as 65%, 80% and 90%. When the percent of training sample is over 80%, the outcomes become quite similar. The number of effective factors also increases with an increasing training sample size and all the effective factors obtained by using small size of training sample are included in the group of effective factors. Thus, this study uses the results based on the training sample being equal to 80% to construct effective indicators for predicting default risk.

where N is the number of factors in the correlaiton matrix in Equation (4). In this study, the correlation matrix is composed of macro factors mentioned in the previous part. It is clear that this method can convert specific correlation matrix to an observation. Since this study focuses on the prediction of indicator, then sliding time windows based on 9 months is used for obtaining the time series of indicator. If there is a time moment t, the indicator $G_{p,\alpha}$ is calculated in the time window $[t-9, t-1]$, which precedes t.

There are two significant parameters in the calculation of indicators. one is the correlation boundary, α; another is the window size for measuring correaltion matrix. In this study, we find that $G_{1,0.5}$ has the best performance of explaning default cycle. In fact, $G_{1,0.5}$ has been widely used by prior studies which has a good performance in the other studies. For example, Gorban et al. (2010) find that the indicator constructed by using $G_{1,0.5}$ captyures the dynamic change of FTSE 100 return in comparison with using the other parameters for p and α to set G.

For the issue of selection of window size, this study uses 6 months, 9 months, 12 months, and 18 months to construct various indicators. The main motivation of using these intervals is twofold. First, past economic crises normally have experienced these lengths of period. Then calculating correlation by using same length of interval is straightforward. NBER's Business Cycle Dating Committee establishes and maintains the chronology of U.S. business cycles and the average recession, and this committee determines that the length of recession tend to average about 9 months if the extremes are eliminated (Kliesen, 2003)[10]. Second, from statistical perspective, short interval can rapidly reflect the changes of correlation in the system and long intervals cannot give the quick response in the current economic conditions since a lot of irrelevant correlation have been considered in the long interval. However, the former one may not be smooth compared with the latter one in terms of plotting the dynamic change of correlations. Thus in this study, the macro indicator based on 9 months is used to capture the changes in macroeconomic conditions. Five indicators based on five groups of macro factors are renamed as indicator.all, indicator.leading, indicator.procyclical, indicator.6.economic, and indicator.effective.

2.3 Basic statistics of IDPs and five indicators

In Table 3, Panel A shows the summary statistics for each variable used in this study. Basically, the value of IDP is quite small after dividing by the number of rated firms. The standard deviation of defaults is quite larger, suggesting that the dispersion is quite high since the largest default month has 37 default events and the smallest default months has no any default events. In contrast, the dispersion for IDP is the smallest among these variables. For these indicators, each statistic value for both indicator.all and indicator.6.economic are almost similar. It means that their distributions are quite similar. The indicator.effective is quite volatile in comparison with the others. It is interesting that the mean values of each variable are greater than that of median values. That is, these variables' distributions are skewed to the right.

The main purpose of filtering IDPs and various indicators is to filter the cyclical component in their time series thereby only keeping their trend component. Consequently, this method can smooth time series and more importantly, the disturbance from zero defaults can be reduced. The filtering method is based on Hodrick-Prescott (HP) filter, and the penalty parameter for smoothing trend is 5 for this study. In Table 3, Panel B shows the summary statistics after using HP filtering method. Basically, the majority of properties found in Panel A can still be found, which means that filtering method does not change the data structure. More importantly, there is no zero value in IDP. After filtering variables, this

[10] Recession is defined as the time from the peak to the trough. It lasted 11 months during the post-World War II period. The shortest of these downturns has lasted 6 months in the beginning of 1980s, while the longest have lasted 16 months for both 1973-75 and 1981-82.

study further transform each variable by building logarithmic ratios in order to transform nonstationary data into stationary ones, following the approach of data transformation proposed by Pfaff (2008).

3. Empirical Results

3.1 Dynamic of macroeconomic conditions and corporate defaults

This part is divided into two parts. The first part is to investigate whether there is a long-run relationship between corporate default risk and macroeconomic environment by using the result from cointegration test. The second part is to further investigate causal relationship between macroeconomic conditions and corporate default risk in different samples. Cointegration test mainly provides cross-check on the validity of the results at the end of the causality analysis. Before proceeding to cointegration test and causality test, this study further splits the sample into 5 different parts in order to consider the structural breaks in either of the time series[11]. There are 5 subsamples determined by using breakpoints method proposed by Bai and Perron (2003)[12]. These points can be seen in Panel F in Figure 2. Also total sample is also investigated. Since this study builds 5 macro indicators for measuring macroeconomic environment, then each indicator and IDP will be investigated individually. Therefore, there are 30 subsamples, and 5 of them covers full sample.

Before analyzing the results from causality analysis, this study initially shows the dynamic change of each macro indicator and IDP in 5 Panels in Figure 2. From Panel A to Panel B, the indicators are constructed by 5 groups of factors and they are all the factors, leading factors, procyclical factors, factors in 6 economic groups and effective factors, representing different types of macroeconomic conditions. All the indicators are blue line in each Panel and IDP is the red line. Four green bars represent four historical NBER economic recessions.

Basically, in each panel the blue line representing macro indicator have similar trend with IDP except two main intervals including the beginning of 1980s and 2000s, suggesting that correlation among macro factors may give the signal of future trend of corporate default risk or measure corporates default risk.

However, for both two intervals including beginning of 1980s and 2000s, this is not the case. Specifically, US economy has experienced three economic recessions. The first one occurred in January 1980 and ended in July 1980, and it lasted 6 months until the US economy returned to growth. However, 1 year later, US economy fell into crisis again. This recession lasted 1 year and 4 months. Both two recessions are initially triggered by higher inflation and 1980 oil crisis. In particular, the inappropriate monetary policy implemented by Federal Reserve contributes to the burst of double-digit inflation in 1980. After that, Federal Reserve undertook tighten monetary policy to curb the higher inflation, which consequently led to dragging the economy into a deep recession (Mishkin, 1995). During this period, many economic sectors, such as manufacturing and construction sectors, have suffered from higher defaults among the firms. However, in the beginning of 1980s there are quite scarce defaults recorded by Moody's, this is also identified by previous studies (Lando and Nielsen, 2010). Thus it seems that all the indicators cannot work well in that period.

From this point, it should be noted that all the indicators are quite volatile in the beginning of 1980s, which means that correlation among these factors are instable and high. Even after 1980s recession, majority indicators have still experienced a higher increase, suggesting that many factors still have higher correlation among each other and macroeconomic conditions are still poor. In fact, this

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[11] Since the number of structural breaks existing in each indicator are less than time series of IDP and these structural breaks are almost covered by that in the time series of IDP, then the influence from no considering the structural breaks in each indicator are minor in this study.

[12] They develop a new algorithm for simultaneously estimate multiple breakpoints. Breakpoints can be regarded as structural changes in the time series, which means that there are some unexpected shifts in the time series. This problem can result in forecasting errors and unreliability of the model in general. This method is more preferable since this method can make regression models including linear and polynomial models working in a stable environment.

phenomenon gets the support from economic literature. For example, Westcott and Bednarzik (1981) propose that the economic recovery after official end of the recession that was established as July 1980 is doubted to a large extent. They argue that “the end of the year again showed a rise in the interest rates to levels that prevailed earlier. While employment had increased steadily over the second half, it had not improved sufficiently in the two industries housing and auto manufacturing-hardest hit in the downturn. Instead, fourth quarter figures for housing sales and auto purchases were relatively weak, giving little hope for a strong improvement in employment in these industries. Also, the unemployment rate had shown very little improvement from the recession high.”

Steven Rattner (1981) reports that “top officials at the Federal Reserve Board, including its chairman, Paul A. Volcker, say that their policy of reducing the expansion of money and credit will mean little or no economic growth in 1981 and continuing high interest rates”. After failing to gain traction during the weak and brief recovery from the 1980 downturn, weakness in manufacturing and housing caused by rising interest rates began to have an expanded effect on related sectors beginning in mid-1981 (Bednarzik et al., 1982). Higher interest rates are able to lead to the other macro factors moving then. Therefore, the correlation among these macro factors is still higher. These arguments provide the reason why there is a high comovement among macro factors or why all the macro indicators are quite high after July 1981.

In the 2000s recession, the peak points in each indicator are lag of the peak point in the series of IDP. It is suggested that higher correlation among macro factors reach the peak level later compared with peak of corporate defaults. Interestingly, IDP reaches the peak in the middle of 2000s recession period and then it decreases rapidly even in the recession period. In contrast, IDP has experienced rapid increase in the 1990s and 2007-2009 financial crisis until the official ending point of recession and then they decrease fast in the nonrecession period.

As mentioned above, although five macro indicators have similar trend with IDP except both two special periods including early of 1980 and 2001, they still have different trends in certain intervals. The peaks of some indicators are ahead of peak of IDP in certain periods. For example, in Panel A in Figure 2, the blue line representing macro indicator constructed by all the factors peak in the official NBER cyclical trough in March 1991, which is same as the IDP. While the peak points in the indicators constructed by the other types of factors in Panel B, C, D, and E follow that in the IDP. Interestingly, both all the indicators and IDP peak in the formal end to the recession in June 2009. In contrast, IDP has a tendency of being ahead of macro indicators in the certain periods except the recession of 2001.

The trend of indicator constructed by all the factors is almost same as the trend of the indicator constructed by the factors in the 6 economic groups, indicating that the comovemnet among these factors from 6 economic groups account for the large weight in the comovement among all the factors. More interestingly, in Panel E, the indicator that is constructed by the set of 29 effective factors seemingly pic the similar trend of IDP, suggesting that historical default crisis can be reflected by dynamic of correlation among certain factors. This result corresponds to the intuition since Lasso is used to extract effective predictors for IDP and then these predictors should have ability of predicting IDP.

In this context, this study further introduces causality analysis to explore whether there is a causal relationship between IDP and each macro indicator thereby identifying the causal relationship between changes in macroeconomic conditions and corporate default risk.

3.2 Long-run relationship between macroeconomic conditions and corporate defaults

From the results of unit root in Table 4, we confirm in which sample IDP and indicator may be susceptible of be cointegrated. It can be seen that there are 12 subsamples that may have cointegration between IDP and macro indicators. They are estimated by Johansen (1988) cointegration test, which is presented in Table 7. The test statistics and asymptotic 5% critical values are shown in Panel A and Panel B. It is interesting that there are only 3 out of 30 samples that have cointegration between IDP and macro indicators constructed by factors from 6 economic groups and effective factors.

Both tests reject the hypothesis of no cointegration ($r = 0$) at the 5% level, whereas they do not reject the hypothesis that $r <= 1$. Therefore, the conclusion is that $r = 1$, that is, there is one stationary relationship between the level of the variables. In particular, 2 subsamples are the full sample. Since the indicator constructed by the factors from 6 economic groups is able to reflect cyclical cycle as using all the factors, then dynamic of comparatively entire macroeconomic conditions tend to be cointegrated with corporate default risk in the long period rather than short period.

In particular, another indicator cointegrated with IDP is constructed by the set of effective factors extracted by Lasso. This result corresponds to the intuition since the effective factors that can highly explain historical default risk from January 1980 to December 2014 should have more explaining power than the other indicators. That is, specific macroeconomic environment has impact on corporate default risk. Cointegrated relationship between IDP and two macro indicators constructed by factors in 6 economic groups and effective factors imply that there must be Granger causality in at least one direction. Then causality tests should be used to further determine the causal relationship between them.

3.3 Causal relationship between macroeconomic conditions and corporate defaults

Table 8 presents the results of causality tests including Granger-causality test and TY causality test. Panel A shows causality results between the indicator constructed by all the factors and IDP. There is no causal relationship in the full sample and subsample from December 1998 to December 2003 since both them are not significant at 5% even 10% significance level. In contrast, in two subsamples including October 1980 – October 1985 and November 1985 – June 1993, we reject that IDP does not Granger-cause indicator based on a significance level of 1% and a significance level of 10%. It is indicated that IDP can provide predictive content of indicator. However, macro indicator can Granger-cause IDP in the two samples including July 1993 – November 1998 and January 2004 – December 2014 since the p-values are highly significant at 1% and 5% significance level.

Panel B shows the results of using indicator constructed by leading factors. There are only two subsamples that have directional relationship between indicator and IDP. For example, in the first interval from October 1980 to October 1985, indicator can Granger-cause IDP; in the next interval, the causal relationship reverses and IDP can provide predicting information for indicator. Then it can be seen that this indicator is not only poor of explaining IDP, but also IDP is also poor of Granger-causing this indicator.

Panel C illustrates the causality results between IDP and macro indicator constructed by procyclical factors. Interestingly, in the subsample from July 1993 to November 1998, there is a bidirectional relationship between indicator and IDP since both two p-values are rejected, suggesting that indicator mutually Granger-cause IDP. Likewise, this indicator can also provide predicting information for IDP in the first interval of total sample, which is same as the indicator constructed by leading factors.

Panel D provides the causality results after using indicator built by the factors in the 6 economic groups for generalized macroeconomic conditions. It is interesting that the results are almost similar as the results from using the indicator constructed by all the factors. There is a difference in the total sample.

Specifically, IDP can Granger-cause indicator if the significance level of 10% is used for rejecting the hypothesis. In fact, if we refer to the p-value in testing the hypothesis of IDP that does not Granger-cause Indicator in Panel A, it is 0.16 which is close to 10%. Then it can be concluded that the results of using all the factors for constructing the indicator are almost same as that of using factors in the 6 economic groups. This suggests that generalized macroeconomic conditions are able to reflect augmented macroeconomic conditions based on all the factors. This may be caused by the number of factors from 6 economic groups that is 104, which is less 10 than all the factors. In fact, this result corresponds to the similar trend between two indicators in Figure 2.

Panel E is a special case compared with the others. First, the indicator is constructed by using only 29 effective factors that are extracted by Lasso. Second, only this indicator can Granger-cause IDP in the full sample since the indicator is significant at 5% significance level. Third, IDP cannot Granger-cause this indicator in any samples. Fourth, like the indicator constructed by all the factors and the factors in the 6 economic groups, this indicator can provide predicting information for IDP in two intervals; however, it cannot predict the last interval but the first interval.

Basically, there are several interesting findings:

1) In using two indicators for measuring relatively complete macroeconomic conditions in Panel A and D, the bidirectional relationship between macroeconomic conditions and corporate default risk is not significant, suggesting that except for no bidirectional relationship between default risk and macroeconomic conditions, the movement of default risk can either result in or result from changes of macroeconomic conditions. Then corporate default risk may be not coincident with changes of macroeconomic conditions. In fact, even using the other indicators representing incomplete and specific macroeconomic conditions, this finding is still consistent.
2) Following the results in Panel A and Panel D, we can conclude that the causal relationship between IDP and macroeconomic conditions is dynamic rather than stable, implying that corporate default risk either interacts with changes of macroeconomic conditions over time or does not interact with dynamic of macroeconomic environment. For example, there is a trend of corporate defaults Granger-causing macroeconomic conditions. Specifically, before July 1993, IDP tends to Granger-cause two indicators, after that, IDP fails to continually provide predicting information for them.

   In particular, even we construct incomplete macroeconomic conditions in the other panels, and this dynamic conclusion still exists. Interestingly, they can Granger-cause corporate defaults in the interval from October 1980 – October 1985. It seems that incomplete macroeconomic conditions may react earlier than the changes of complete economic conditions.

   No matter how to construct the indicators for measuring macroeconomic conditions, changes of macroeconomic conditions fail to provide any predictive content for the changes of default risk in the period from December 1998 to December 2003, and even corporate default risk also fail to Granger-cause macroeconomic conditions, indicating that there is no any causal relationship between corporate default risk and macroeconomic conditions. This is consistent with the finding in Figure 2 since the peak of each indicator in each Panel is behind of the peak of IDP in the recession of 2001. Thus, we can conclude that the predictability of both complete and incomplete macroeconomic conditions to corporate default risk is time-varying rather than consistent over time.
3) The indicator constructed by effective factors for measuring specific macroeconomic conditions outperforms the other indicators in terms of Granger-causing IDP even in the full sample. It is suggested that historical change of default risk can be influenced by the certain economic environment that is represented by the key set of economic variables. The results of

time-varying predictability of specific macroeconomic conditions to corporate defaults are even clearer than using the other types of macroeconomic conditions. The best combination of effective factors can have predicting information for corporate defaults in the full sample; however, it cannot consistently have this power to predict default risk in each interval.

3.4 Investigation of how macroeconomic conditions explain corporate defaults

This part is to test whether the following three hypotheses are right or not in support of theoretical finding of whether and how macroeconomic conditions explain corporate defaults. The analysis is based on two approaches. One is to use both two IDP and each indicator without any lags. Another approach is to further verify whether both macro indicators and NBER economic recessions have predictive ability for IDP 3 months ahead. After removing small default events, the number of total observation is reduced from 411 to 169. Three hypotheses are tested below:

1. *Hypothesis 1: Can macro indicators explain corporate default risk?*
2. *Hypothesis 2: Can economic recession as a special scenario explain corporate default risk?*
3. *Hypothesis 3: Is there an additive effect between macro indicators and economic recessions on predicting corporate default risk?*

(1) First approach: no lags in each variable

Table 9 shows the regression results. Basically, five macro indicators and recession are all significance in explaining IDP, suggesting that both changes of macroeconomic conditions and recessions can explain higher default risk. The interaction items defined as indicator times recession are significance in using 5 macro indicators and they are all negative. It means that in the recession period, changes of a unit of indicator should have less effect on IDP compared with that effect on IDP in the non-recession period. That is, changes of defined macroeconomic environment have different effects on corporate default risk in recession and non-recession.

Now it is interested to investigate the unique effect of each indicator on IDP. From Panel B in Table 9, if there is no recession, the indicator constructed by effective factors has the largest unique effect on IDP with coefficient being equal to 0.62, which is followed by all the factors (0.616), factors in the 6 economic groups (0.597), procyclical factors (0.558), and leading factors (0.537).

If there is recession, the unique effect of each indicator on IDP is the sum of $\beta_1 + \beta_3$ which is shown in Panel C. Then for the indicator constructed by all the factors, leading factors, procyclical factors, factors in 6 economic groups and effective factors, the unique effects are 0.053, 0.174, 0.036, 0.056, 0.05, respectively. It is clear that the unique effects of each indicator on IDP in the recession are quite smaller than their effects on IDP in the non-recession period. That is, a rapid change of economic environment has larger effect on explaining changes of default risk in the non-recession period; however, it has smaller effect on predicting changes of default risk.

This finding can be interpreted as below. The NBER's Business Cycle Dating Committee defines NBER recession. This committee examines and compares the behavior of various measures of broad activity: real GDP measured on the product and income sides, economy-wide employment, and real income and they also may consider indicators that do not cover the entire economy, such as real sales and the Federal Reserve's index of industrial production. If these indexes increase or decrease consecutively, then NBER recession is defined. Then economic recession is a special scenario in the evolution of economic environment. Figure 2 shows that macro indicators have experienced rapid increase in each recession except the recession occurred in early of 1980s. While the peaks of IDP exist during the recession period, it can be expected that there is an interaction between NBER recessions and macro indicators.

In this context, changes in macroeconomic conditions, as reflected by changes in interest rates, the stock market indexes, exchange rates, unemployment rates, etc. may impact the overall profitability of firms. Consequently, the exposures of the various lead to financial unhealthy in each obligor and the increase of the probabilities of default and of migrating from one credit rating to another (Crouhy et al., 2000). Then corporate default risk increase during this period. Macro indicator increases, and the policy makers tend to define the worst economic situation occurring. Thus the additive effect between recession and indicator is quite small.

Another interesting finding is about the predicting power of these independent variables on IDP. Adjusted R-squared is used for investigation in this case. It is clear that the indicator constructed by effective factors and recession and their interaction item have the largest predicting power on IDP with Adjusted R-squared being equal to 38%, which is followed by using indicators constructed by all the factors (36%), factors in the 6 economic groups (35%), leading factors (32%), and procyclical factors (30%).

Figure 5 provides the results of model diagnostics. Panel A shows two sets of information. One is about the residual and fitted plot; another is QQ plot for the normality test in the residual. For the residual vs fits plot, this is a scatter plot of residuals on the y axis and fitted values (estimated responses) on the x axis. Basically, majority plots illustrate that the scatter points seemingly cluster in the right side of each graph. However, it seems that the residuals randomly distribute around the 0 line especially for Panel A1, Panel A4, and Panel A5. Then it can be concluded that the assumption that the linear relationship seems to be reasonable. In addition, the residuals do not likely form a horizontal band around the 0 line since the blue line in each graph are not purely along the zero line. Then this study uses heteroscedasticity test to further test whether the residual is constant or not. Since all the p-values are larger than 10%, then the null hypothesis of constant in the error term is not rejected. Thus the variances of the error terms in each model are equal. QQ plot is used to test whether the residuals follow normal distribution. It can be seen that all the points on the q-q plot fall approximately on a straight line in Panel A1, Panel A3, and Panel A4. Two cases are not really good which are in Panel A2 and Panel A5 since there are several points beyond 5% area. That is, we may reject null hypothesis of normality in the significance level 5%. Then from these results, we can basically conclude that majority models are fitted well. Particularly, the indicator constructed by all the factors and the factors in the 6 economic groups are well fitted compared with the others.

Therefore, it can be concluded that three hypotheses are reasonable. Both changes of various macroeconomic conditions and recession can provide predictive content on the default risk. There is an additive effect between them. In the recession period, the unique effect of different types macroeconomic conditions on higher corporate default risk is smaller than that in the non-recession period. The indicators constructed by effective factors, all the factors and factors from 6 economic groups have the largest predicting power with recession and their interaction item. From results of causality tests, it can be seen that these three indicators provide more predictive content than the other types of indicators. That is, these results correspond to the findings from causality analysis since they have more causal relationships in different intervals. Specific economic environment outperforms non-specified one, even the augmented and generalized macroeconomic environment.

(2) Second approach: lag indicator and economic recession by 3 months

Table 10 shows the regression results after lagging indicator and NBER recession by 3 months. Compared with the results in Panel A in Table 9, the basic findings are almost same. Specifically, five macro indicators and recession are still significance in explaining IDP, suggesting that both changes of various macroeconomic conditions and recessions can predict default risk 3 months ahead.

Essentially, the method of constructing indicator in the data description part gives the predicting power for this indicator, that is, macroeconomic conditions definitely can predict default risk based on the results in Table 9. In this case, this study further lags indicator and recession as the dummy variable by 3 months, suggesting that there is extra 3 months' early sign in the changes of the economic environment, which can still predict corporate default risk.

In Panel A, although both NBER recessions and indicators can still predict IDP, it is not the same case for the interaction items between them. None of them are statistically significant, which means that there is no interaction effect between lagged indicator and lagged NBER recession.

For the results of adjusted R-squared, the largest one is still from using the indicator constructed by effective factors. Interestingly, the second best indicator is constructed by leading factors, and its adjusted R-squared increase from 0.319 in Table 9 to 0.331 in Table 10. In contrast, the other corresponding values of adjusted R-squared decrease, for example, adjusted R-squared for the indicator constructed by effective factors reduce from 0.383 to 0.332 by 0.051. The value of adjusted R-squared constructed by all the factors goes down to 0.321 by 0.033 from 0.354. Likewise, for the indicator built by factors in the 6 economic groups, adjusted R-squared value decreases from 0.346 to 0.317 by 0.029.

This finding of why there is an improvement in the lagged indicator constructed by leading factors for explaining IDP can be interpreted from the economic perspective. Majority macroeconomic factors used in this study are cyclical factors, which can be classified into three different groups including leading, coincident, and lagging indicators based on the timing of their movements. Leading factors move in the early stage than the other factors such as lagging and coincident factors and they tend to move direction before the business cycle occurs and the timing comparisons between the cyclical turn in the indicators and business cycle turn is one month or more, such as, new orders, housing starts, and consumer sentiment (Shiskin and Moore, 1967). This is why this indicator performs well after lagging by 3 months, and the other indicators lose the original power of explaining IDP. The rest of indicators are constructed by all the factors, factors in 6 economic groups, and procyclical factors and this ranking order is same as using IDP and indicator without any lags shown in Table 9.

Figure 6 provides the diagnostics results of models in Table 10. Basically, for the residual vs fits plot, majority plots illustrate that the scatter points seemingly cluster in the right side of each graph. However, it seems that the residuals randomly distribute around the 0 line. Then it can be concluded that the assumption that the linear relationship seems to be reasonable. In addition, the residuals do not likely form a horizontal band around the 0 line since the blue line in each graph are not purely along the zero line in the left side of each graph. Then this study uses heteroscedasticity test to further test whether the residual is constant or not. Since all the p-values are larger than 5%, then the null hypothesis of constant in the error term is not rejected. Thus the variances of the error terms in each model are equal. QQ plot is used to test whether the residuals follow normal distribution. It can be seen that all the points on the QQ plot fall approximately on a straight line. Then from these results, we can basically conclude that majority models are fitted well.

Therefore, it can be concluded that the first two hypotheses are still reasonable. Both changes of each indicator and recession can provide predictive content on corporate default risk by 3 months ahead. However, the additive effect disappears after lagging indicator and economic recession by 3 months. That is, the unique effect of changes of each indicator on corporate default risk is constant either in the recession or in the non-recession period. The indicator constructed by leading factors may have strong predicting power compared with the other types indicators, which is followed by the indicator constructed by using leading factors, all the factors, and factors from 6 economic groups, and procyclical factors. Then we can conclude that incomplete macroeconomic conditions still have a power of explain default risk compared with specific and augmented and generalized macroeconomic conditions.

4. Discussions

4.1 Why there are interactions between macroeconomic conditions and corporate defaults?

As discussed early, prior studies on the causal relationship between corporate default risk and macroeconomic conditions reach two conclusions: (1) corporate defaults exert a powerful effect on the economy, which leads to the economy slowdown and macroeconomic conditions become worse, and (2) macroeconomic conditions can affect corporate defaults; that is, deteriorated macroeconomic conditions result in corporate defaults. Although space does not permit an exhaustive discussion of the complex debates that have raged about both of these questions, this study summarise some main points and attempt to classify between these issues and the themes examined in this research.

The causes of how corporate defaults have impact on the macroeconomic conditions can be interpreted by twofold. One reason is that if corporate defaults are caused by credit market frictions, then this is the case. Credit market frictions are related to the theory of imperfect market that is proposed by Jensen and Meckling (1976). Bernanke et al. (1994) regard the phenomenon of imperfect information as credit market frictions. The degree of credit market frictions results in the changes of credit market conditions measured by firm defaults. Deteriorated credit market conditions have great impact on the economy, that is, it can depress economic activity (Gertler, 1988, Bernanke et al., 1994). Bernanke (1993) argues that the savings and loans crisis in the 1980s and 1990s is a good example of corporate defaults making economy worse. The federal deposit insurance provides the extensive credit to the savings-and-loan institutions without enforcing sufficient limits on the riskiness of savings-and-loan investments. Many saving-and-loan owners are motivated to engage on highly levered and risky portfolios of long-term loans, mortgage-backed securities, and other risky assets. Then it is clear that if these investments are success, the owners can gain a lot; otherwise, they can lost a lot. Consequently, numerous corporate defaults trigged by this case make severity of economic downturns. In fact, our results strongly provide empirical support and the two intervals covering two recessions in the 1980s and 1990s show that corporate default risk tends to Granger-cause the macroeconomic conditions in Panel A and D in Table 8.

The second reason is that firm-specific factors and productivity shocks are able to affect firm defaults proposed by Bernanke et al. (1999). They initially propose a theoretical framework to explain how corporate defaults make macroeconomic conditions worse. They explain that if the firms suffer from a productivity shock, then there will be a decline in cash flow thereby being be able to finance fewer inputs and less productivity. Lower production implies lower profits that propagates the effects of the initial decrease in cash flow. Greenwald and Stiglitz (1988) determine that these financial factors may impact on the level of inputs, such as employment or inventories, as well as the level of capital investment. Meanwhile, the value of their lands and collaterals decrease. This results in the tightened borrowing constraints, less production and spending. Consequently, the value of their collaterals and lands will be reduced further, which deeply propagates the shock to the economy. Many empirical studies have determined that firm-specific factors such as accounting ratios have significant explanatory power for credit losses, spreads and corporate default rates via reduced-form models (Altman, 1968, Ohlson, 1980, Zmijewski, 1984, Shumway, 2001, Chava and Jarrow, 2004, Campbell et al., 2008).

For the causes of macroeconomic conditions that have impact on default risk, a seminal study that is done by Hackbarth et al. (2006) determine how macroeconomic conditions affect default risk and they state that since firm defaults are endogenous in endogenous default structural models (Black and Cox, 1976, Leland, 1994, Leland and Toft, 1996, Acharya and Carpenter, 2002), the decision of whether firm is going to default depends on the shareholder’s default policy that is represented by various default threshold for each economic state. Once debt has been issued, shareholders have the option to default on their obligations. Hackbarth et al. (2006) further explain that default threshold is strongly associated with two main elements including tax benefit and bankruptcy costs. The former one depends on the level of cash flow, which in turn depends on macroeconomic conditions since in boom the cash flow tends to be higher; however, in bust it is quite lower. The latter one is dependence of the probability of default and the loss given default, which all depend on the current macroeconomic conditions. Then macroeconomic conditions can have a great influence on corporate defaults.

Another theoretical study done by Chen (2010) reaches same conclusion, which provides another mechanism to explain this phenomenon. He focuses on the effects of time varying risk premia on firms' financing decisions and the pricing of corporate bonds. He further explain dynamic of default boundaries based on Hackbarth et al. (2006)' study and figure out why firms choose higher default boundaries in bad period. Since decision of default is similar as exercising a put option. In bad economic stage, the risk premia of a put option are quite higher, and the expected growth rates of cash flows are also lower. Consequently, equity holders have a strong tendency of default in face of reduction in the present value of future cash flows. If the firm's cash flows highly correlate with the market, then the changes of macroeconomic conditions will have a large impact on their cash flows. As a result, defaults have a strong tendency of occurring in bad macroeconomic conditions, which lead to the increase of credit spread and decrease of the firm's incentive to hold debts.

Several studies find that changes of monetary policy representing macroeconomic conditions have strong impact on corporate defaults via its effect on inflation or deflation (Bhamra et al., 2011, Fisher, 1933, Wadhwani, 1986). Bhamra et al. (2011) figure out that the financial crisis of 2007-2008 is a good example for proving how these changes have had a severe impact on both the default rates and credit spreads of firms, which corresponds to our finding since macroeconomic conditions tend to Granger-cause corporate default in Panel A and D in Table 8.

4.2 Why there are no interactions between macroeconomic conditions and corporate defaults from March 2001 to November 2001?

Compared with prior studies, we find that there is no causal relationship between any types of macroeconomic conditions and corporate defaults in the recession occurred in March 2001. Actually, this finding corresponds to the findings in the economic literature. This primary reason is due to the unique feature of this recession.

First, the recession that started in March 2001 is different from other recessions of the past thirty years. As discussed earlier, the past two recessions in the early 1980s are caused by monetary policies undertaken by Federal Reserve. The recession of 1990 was caused by the consumption shock and this shock is related to the response of consumers in face of uncertainty raised by Irap's invasion of Kuwait and 1979 oil crisis. The cause of 2007 was the housing boom and bust which in turn led to financial turmoil in U.S. Taylor (2009) argues that this financial crisis is caused by the government actions and interventions through excess monetary policies. Then it can be seen that the cause of financial crisis that began in 2007 is similar as the twin recessions of the early 1980s. Stock and Watson (2003) explain that "the recession of 2001 started neither in the shopping mall nor in the corridors of the Federal Reserve Bank, but in the boardrooms of corporate America as businesses sharply cut back on expenditures—most notably, investment associated with information technology—in turn leading to declines in manufacturing output and in the overall stock market".

Figure 3 shows the percent of defaulters located in the specific industrial groups in the industrial firms by Moody's 11 industrial categories in 9 intervals. Three pies charts in the middle of graph shows the three recession intervals including 1990, 2001, 2007, respectively. Then the other two intervals located in both right and left side of each recession interval are ahead of 8 months and lag of 8 months. It can be seen that for the recession 1990 and 2007, the main defaulters are from capital industries and consumer industries. However, for the recession of 2001, technology, unassigned firms, and capital industries account for the largest amount in each pie. Combining the preliminary finding in Figure 2, it can be concluded that macroeconomic conditions seemingly capture the default risk in the capital industries and consumer industries, and they cannot capture the defaults occurring in the technology industrials and unassigned firms. For the group of unassigned groups, many firms are related to technology and communication sectors. It is clear that productivity shock may have less effect on these firms compared with consumer industries and capital industries; that is, corporate defaults do not seemingly impact macroeconomic conditions. Therefore, the types of industry that defaulters are located in depends on the interaction between macroeconomic conditions and corporate defaults.

Another big difference in comparison with the other recessions is that why the high correlation among these factors occurred later than the recession even the peak of corporate default risk. Basically, recessions occur since economic developments are not of insufficient magnitude to alter expenditures by households and firms so as to decrease aggregate demand, output, and employment (Kliesen, 2003). Then it is suggested that when there is an occurrence of recession, many macro factors move in the way, which shows deterioration of macroeconomic conditions. Thus, their correlation among various factors is quite high. This is the case in the early 1980s crises, 1990 crisis, and 2007 crisis. However, the recession occurring in March 2001 does not follow the same path.

Kliesen (2003) explains that the unique feature of this crisis is its mildness, for example, the decline in nonfarm employment was well below average, the civilian unemployment rate increased by less than normal, and the increase of real personal consumer spending was relatively larger than the average postwar recession. In addition, although there was a decline in industrial production that peaked in June 2000 and manufacturing and trade sales fell during the first quarter of 2001, employment did not reach the peak until March 2001 as the starting point of 2001 recession. The decline in personal income indicated that the unusual fact that productivity growth remained strong through this crisis. Real GDP even increased 0.2 percent from the first quarter of 2001 to the fourth quarter of 2001. That is, during the recession period, real GDP still grew. Stock and Watson (2003) identify that “the economy gained substantial strength in the final quarter of 2001 and throughout 2002, and all the monthly indicators were growing by December 2001.” Then, the higher correlation appears after December 2001. In particular, they also determine that the majority of leading indicators lose the ability of predicting the economic recession in March 2001, which proves that the poor performance of indicator built with leading factors in Panel B in Figure 2.

4.3 Can we find the evidence of supporting AMH hypothesis from credit market?

In fact, this dynamic change of interactions between corporate defaults and macroeconomic conditions provide strong empirical support of adaptive market hypothesis (AMH) proposed by Lo (2004) in terms of the performance of investment strategies that depends on the certain environments. That is, the predictive ability of macroeconomic conditions to corporate defaults is changing over time.

An obvious example is to use specific macroeconomic conditions to do causality analysis with corporate defaults, which shows how specific macroeconomic conditions Granger-cause corporate defaults over time. Since the effective factors are extracted based on 35 years full sample, then these factors should have predictive content for corporate defaults. Following AMH, the performance of specific macroeconomic conditions should decline for a time and then return to predictability, when environment conditions become more conductive to such construction of macroeconomic conditions. Then, in the full sample, specific macroeconomic conditions definitely have predicting information for corporate defaults in the total sample. However, in the specific intervals, the performance of this indicator is time-varying rather than constant. Likewise, using other macroeconomic conditions, this phenomenon still exists, which means that this is not exceptional case but a rule.

It should be noted that the no predicting power for macroeconomic conditions, which is consistent with EMH, cannot be interpreted as a simple towards efficiency but drives the other market changes. As mentioned previously, firm defaults can be caused by two main factors including macroeconomic shocks and firm-specific factors. Firm-specific factors are related to defaults that may be caused by credit market frictions. Then in this study, it can be seen that before July 1993, macroeconomic conditions have no predicting power for corporate defaults since Bernanke (1993) argues that corporate defaults are caused by asymmetric information between borrowers and lenders, and many loans are used to invest in the high risky project that are not consistent with the contract.

According to AMH, in this dynamic change of market, market participants may survive or die through their heuristics responding to the changes of environments. For example, firm defaults depend on their understanding of default boundaries which depends on macroeconomic conditions; that is, defaults can be decided by the firms more exactly equity holders. The results of default or no default reflect whether the market participants adapt to the changes of economic environment[13]. Environments consist of from macro level to micro level of economy and from economic conditions to social conditions. Therefore, in order to achieve a consistent level of predicting power, we need to change the combination of factors, which can adapt to changing market conditions.

4.4 Can we construct an early-earning system for capturing potential defaults based on various indicators representing different types of macroeconomic conditions?

By using different types of macroeconomic conditions, we find that two indicators representing relatively complete macroeconomic conditions have more causal relationship with corporate default risk and the prediction power with NBER recessions are also larger than using the other two indicators representing incomplete macroeconomic conditions except lagged indicator constructed by lead factors.

These results not only are consistent with ignition, but also support theoretical finding of Shiskin and Moore (1967) and Scheffer et al. (2012). If more macro factors can be considered in the business cycle analysis, then we are able to capture any changes in economic activities impacted by unpredictable macroeconomic shocks. In addition, these shocks can be reflected by critical transitions in the macroeconomic system. Then we can conclude that incomplete macroeconomic conditions cannot pic entire economic process but portion of economic process.

Since specific macroeconomic conditions are more compatible with the default history and they can show the perception of past default risk, then even specific macroeconomic conditions have predictive ability in the full sample with largest predicting power among various macroeconomic conditions, and corporate defaults should have no any predictive content for specific macroeconomic conditions. However, it is undoubted that these effective factors can only reflect what happened in the past but fail to show what happen in the future since defaults are stochastic events and are unpredictable, specific macroeconomic condition is limited to explain default risk in the past rather than the future. Then relatively complete macroeconomic conditions are more preferable for predicting corporate defaults in practice. It should be noted that after lagging 5 macro indicators, only the indicator constructed by leading factors increases predicting power on default risk, which implies that incomplete macroeconomic condition may still be used as a supplementary tool for predicting corporate defaults.

After removing small default events, five macro indicators and NBER recessions are all highly significance in explaining corporate defaults. Even we lag both indicators and recession by 3 months,

[13] In AMH theory, if a firm defaults in the end, it means that this firm cannot adapt to the changes of market conditions, which is called as maladaptive.

and they are still highly significance. This finding provides strong empirical support on the theoretical studies including Chen (2010) and Hackbarth et al. (2006). That is, macroeconomic conditions can make corporate defaults worse in practice.

To sum up, we may build an early-warning system for predicting corporate defaults based on these macro indicators especially for the indicator constructed by all the macro factors, even though the predicting power is limited to the defaults trigged by macroeconomic shocks with around 35 % predicting power.

5. Conclusion

This paper successfully introduces a cutting-edged technique used for capturing critical transitions from nature science in order to measure changes of macroeconomic conditions. Then we investigate the interaction between various macroeconomic conditions and corporate defaults, identify why these interactions between them can provide empirical support of AMH, determine how various macroeconomic conditions can impact corporate default risk and how much power various macroeconomic conditions have in terms of predicting corporate defaults.

We find that the interactions between macroeconomic conditions and corporate defaults are dynamic. Specifically, current theory suggests that in the savings and loans crisis in the 1980s and 1990s, corporate defaults make macroeconomy worse. Our results provide empirical evidence since corporate defaults have predictive contents on macroeconomic conditions in the intervals covering that two recessions. Meanwhile, our results show that macroeconomic conditions make corporate default worse in the interval covering the 2007-2008 recession, which is also consistent with the argument in the early literature. However, we find that there is no interaction in the interval covering the recession occurring in March 2001, which has not been mentioned in the early studies. We find that in this period, during the whole recession, the economy still grows. Additionally, majority of defaulters are from technology sector, which is not the same case in the other recessions since they are mainly from consumer and capital sectors. Then we conclude that the interaction between them may depend on specific economic sectors. More significantly, based on aforementioned results, our study successfully proves that AMH hypothesis is reasonable in the credit market, since the predictive power of macroeconomic conditions to corporate defaults is time-varying.

This paper also provides a framework of proving in which scenarios macroeconomic conditions can impact corporate defaults. After removing small default events that my not trigged by macroeconomic environment, we find that 5 indicators with recession are significance in explaining corporate defaults and there is interaction effects between each indicator and recession. Even we lag indicators and recession by 3 months, they are still highly significant. These results are consistent with recent theoretical findings of macroeconomic conditions that make economy worse (Hackbarth et al., 2006, Chen, 2010).

By comparing with the performance of each indicator in terms of predicting corporate defaults, the results provide support for the importance of considering more macro factors in order to capture any changes in the macroeconomic conditions. This is because broad economic factors can consecutively detect the potential changes in the macroeconomic environment, even though some factors that had better performance in the past deteriorate in the present. Another reason is that we could obtain a long, high-resolution data, which can help detect incipient transitions from time series. These results provide shed light on building an early-warning system for predicting corporate defaults by constructing macro indicators.

For the future study, it is challengeable of how to construct more effective indicators to improve predicting performance on corporate defaults. There are two main issues. First, Helbing (2013) argues that “The increasing availability of ‘big data’ has raised the expectation that we could make the world more predictable and controllable. Indeed, real-time management may overcome instabilities caused by delayed feedback or lack of information. However, there are important limitations: too much data can make it difficult to separate reliable from ambiguous or incorrect information, leading to misinformed decision- making. Hence too much information may create a more opaque rather than a more transparent picture.” Then how to use such a big amount of factors for constructing the indicator is a new question.

Second, Figure 7 shows the risks interconnection map 2011 illustrating systemic interdependence in the hyper-connected world we are living in, taken from Helbing (2013). Then it is clear that credit crunch/liquidity that is used to measure credit market conditions has five main direct connections with asset price collapse, fiscal crisis, global imbalances and currency volatility, extreme consumer price volatility, and regulatory failures. However, these five terms are highly correlated with the other types of risks. Meanwhile, AMH also suggests that a better way of achieving a consistent level of predicting power is to adapt to changing market conditions by allowing for various factors. Therefore, how to construct default risk indicator by effectively and efficiently using various data, such as macro factors, micro factors, political factors, and environmental factors is the another challenge in term of predicting future collapse in the credit market.

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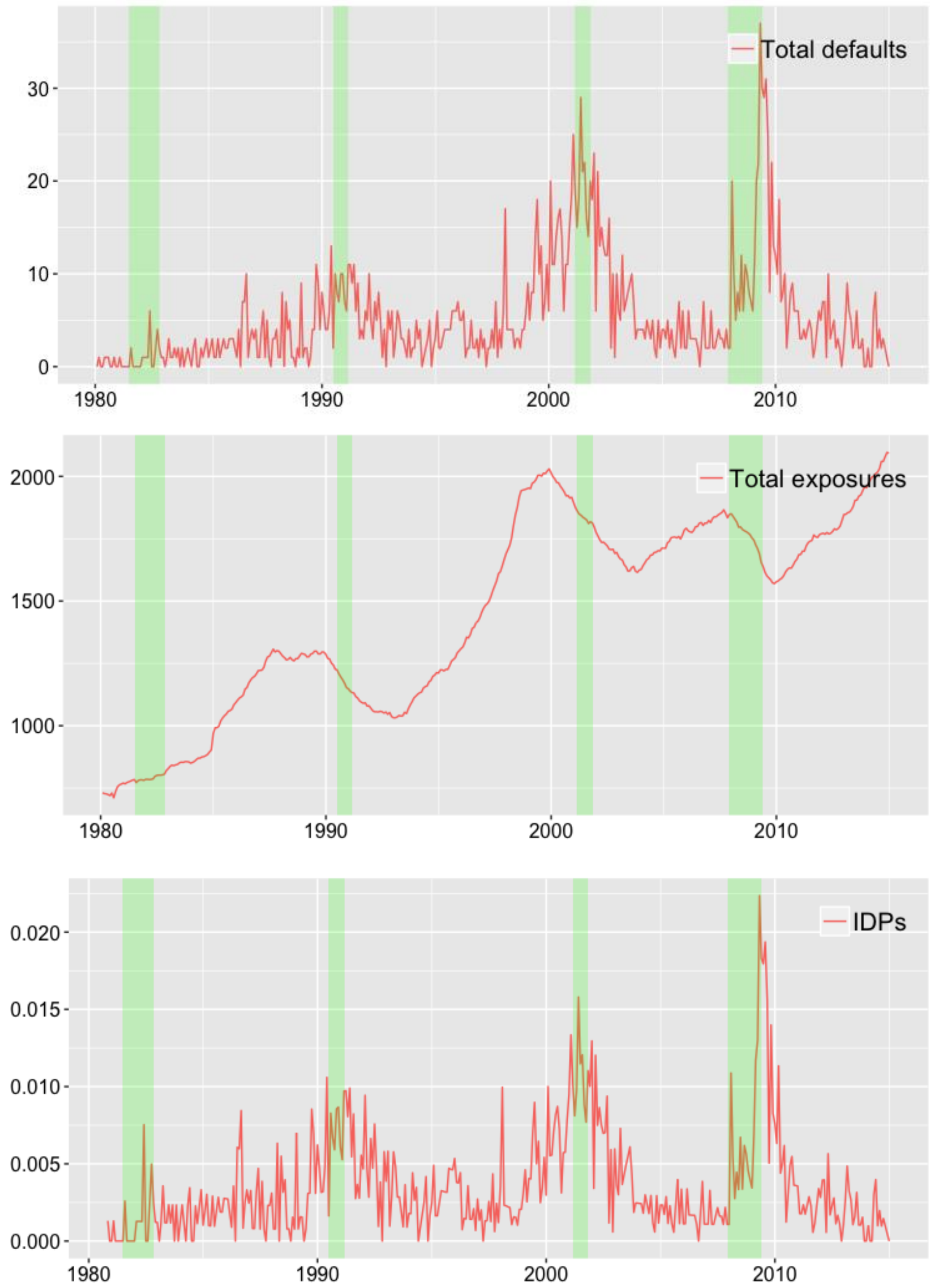
Figure 1 Time series of monthly default data in US industrial firms from January 1980 to December 2014.



This figure shows time series of total defaults, total exposures, and IDPs in US industrial firms from January 1980 to December 2014. IDPs are fractions in which the numerator represents the number of issuers that defaulted in a particular time period in the first graph and the denominator represents the number of issuers that could have defaulted in that time period in the second graph. The formula of IDP in the third graph is shown below: $IDPs = d_t^{IDP}/n_t^{IDP}$, where $n_t^{IDP} = n_{t-1}^{IDP} - d_{t-1}^{IDP} - w_t^{IDP}$. The numerators d_t^{IDP} and d_{t-1}^{IDP} are the numbers of issuers defaulting at period t and $t-1$. The denominators n_t^{IDP} and n_{t-1}^{IDP} are the numbers of issuers that potentially could have defaulted at date t and $t-1$. w_t^{IDP} denotes the number of credits which withdraw between periods t and $t+1$ (Acharya and Carpenter, 2002, Gansecki, 2010, Moody, 2015) .

Table 1 Data description for macro factors

Summary listing	Factors										Total
	Full name	**Abbreviation**	**Cyclical factor**	**Relation with business cycle**	**8 Economic groups**	**Full name**	**Abbreviation**	**Cyclical factor**	**Relation with business cycle**	**8 Economic groups**	
	Macro and BC conditions (85 factors)										
	Loans and Leases in Bank Credit, All Commercial Banks	LOANS	Lagging factor	Procyclical	MC	Household debt/income-ratio	TDSP	Lagging factor	Countercyclical	MC	
	Real Estate Loans, All Commercial Banks,1943	REALLN	Lagging factor	Procyclical	MC	Household obligations/income	FODSP	Lagging factor	Countercyclical	MC	
Bank lending conditions	Total Consumer Credit Owned and Securitized, Outstanding	TOTALSL	Lagging factor	Procyclical	MC	Interbank Loans, All Commercial Banks	IBLACBM027S BOG	Lagging factor	Procyclical	MC	11
	Commercial and Industrial Loans, All Commercial Banks	BUSLOANS	Lagging factor	Procyclical	MC	Borrowings, All Commercial Banks	BOWACBM027 SBOG	Lagging factor	Procyclical	MC	
	Consumer Loans at All Commercial Banks	CONSUMER	Lagging factor	Procyclical	MC	Required Reserves of Depository Institutions	REQRESNS	Lagging factor	Countercyclical	MC	
	Federal Debt: Total Public Debt	GFDEBTN	Lagging factor	Countercyclical	MC						MC
	Economic activity index	USPHCI	Coincident factor	Procyclical	PICT	Real Manufacturing and Trade Industries Sales	CMRMTSPL	Coincident factor	Procyclical	PICT	
	Industrial Production Index	INDPRO	Coincident factor	Procyclical	PICT	Smoothed recession probabilities	RECPROUSM1 56N	Coincident factor	Countercyclical	NA	
	Industrial Production: Mining: Drilling oil and gas wells	IPN213111S	Coincident factor	Procyclical	PICT	Uni Michigan consumer sentiment	UMCSENT	Leading factor	Procyclical	NA	
	Industrial Production: Manufacturing (SIC)	IPMANSICS	Coincident factor	Procyclical	PICT	Real final sales of domestic product	A190RL1Q225S BEA	Leading factor	Procyclical	PICT	
	Industrial Production: Mining	IPMINE	Coincident factor	Procyclical	PICT	Final Sales to Domestic Purchasers	FSDP	Leading factor	Procyclical	PICT	
	Industrial Production: Electric and Gas Utilities	IPUTIL	Coincident factor	Procyclical	PICT	Expenditure durable goods	PCEDG	Leading factor	Procyclical	PICT	
	Industrial Production: Materials	IPMAT	Coincident factor	Procyclical	PICT	New One Family Houses Sold	HSN1F	Leading factor	Procyclical	FCI	
	Personal income	PI	Coincident factor	Procyclical	PICT	Capacity Utilization: Manufacturing (NAICS)	MCUMFN	Leading factor	Procyclical	PICT	
General macro indicators	Real disposable personal income	DSPIC96	Coincident factor	Procyclical	PICT	Capacity Utilization: Total Industry	TCU	Leading factor	Procyclical	PICT	36
	Personal Consumption Expenditures	PCE	Coincident factor	Procyclical	PICT	Moving 12-Month Total Vehicle Miles Traveled	M12MTVUSM2 27NFWA	Leading factor	Procyclical	PICT	
	Personal Consumption Expenditures: Chain-type Price Index	PCEPI	Coincident factor	Procyclical	PICT	Light Weight Vehicle Sales: Autos & Light Trucks	ALTSALES	Leading factor	Procyclical	PICT	
	Government expenditure	W068RCQ027 SBEA	Coincident factor	Countercyclical	INIV	Housing Starts	HOUST	Leading factor	Procyclical	FCI	
	GDP	GDP	Coincident factor	Procyclical	PICT	Building Permits	PERMIT	Leading factor	Procyclical	FCI	
	Gross private domestic investment	GPDI	Coincident factor	Procyclical	FCI	ISM Manufacturing: New Orders Index	NAPMNOI	Leading factor	Procyclical	FCI	
	Private Nonresidential Fixed Investment	PNFI	Coincident factor	Procyclical	FCI	ISM Manufacturing: Inventories Index	NAPMII	Leading factor	Procyclical	INIV	
	Change in private inventories	CBI	Leading factor	Procyclical	INIV	ISM Manufacturing: Supplier Deliveries Index	NAPMSDI	Leading factor	Procyclical	PICT	
	Private Residential Fixed Investment	PRFI	Coincident factor	Procyclical	FCI	ISM manufacturing index	NAPM	Leading factor	Procyclical	PICT	
	Gross National Product	A001RP1Q027 SBEA	Coincident factor	Procyclical	PICT	The months' supply is the ratio of houses for sale to houses sold.	MSACSR	Leading factor	Countercyclical	PICT	
	Initial Claims	ICSA	Leading factor	Countercyclical	EU	Civilian Employment	CE16OV	Coincident factor	Procyclical	EU	
	Weekly Hours Worked: Manufacturing for the United States	HOHWMN02U SM065S	Leading factor	Procyclical	EU	All Employees: Total Nonfarm Payrolls	PAYEMS	Coincident factor	Procyclical	EU	
	Employment Level: Part-Time for Economic Reasons, Slack Work or Business Conditions, Nonagricultural Industries	LNS12032198	Leading factor	Procyclical	EU	All Employees: Manufacturing	MANEMP	Coincident factor	Procyclical	EU	
Labour market conditions	ISM Manufacturing: Employment Index	NAPMEI	Leading factor	Procyclical	EU	Average (Mean) Duration of Unemployment	UEMPMEAN	Lagging factor	Countercyclical	EU	13
	Civilian Unemployment Rate	UNRATE	Coincident factor	Countercyclical	EU	Of Total Unemployed, Percent Unemployed 27 Weeks and over	LNU03025703	Lagging factor	Countercyclical	EU	
	Labor Market Conditions Index	FRBLMCI	Coincident factor	Procyclical	EU	Number of Civilians Unemployed for 15 Weeks & Over	UEMP15OV	Lagging factor	Countercyclical	EU	
	Civilian Employment-Population Ratio	EMRATIO	Coincident factor	Procyclical	EU			Coincident factor	Procyclical	EU	
	Gross Saving	GSAVE	Coincident factor	Procyclical	MC	Consumer Price Index for All Urban Consumers: Housing	CPIHOSSL	Lagging factor	Procyclical	PCP	
	Gross Private saving	GPSAVE	Coincident factor	Procyclical	MC	Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	Lagging factor	Procyclical	PCP	
	Personal Saving	PMSAVE	Coincident factor	Procyclical	MC	Monetary Base	BOGMBASE	Leading factor	Procyclical	MC	
	GDP deflator, implicit	GDPDEF	Coincident factor	Procyclical	PCP	M1 Money Stock	M1SL	Leading factor	Procyclical	MC	
Monetary policy indicators	University of Michigan Inflation Expectation	MICH	Leading factor	Procyclical	PCP	M2 Money Stock	M2SL	Leading factor	Procyclical	MC	15
	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy	CPILFESL	Lagging factor	Procyclical	PCP	M3 for the United States	MABMM301US M189S	Leading factor	Procyclical	MC	
	Consumer Price Index for All Urban Consumers: Energy	CPIENGSL	Lagging factor	Procyclical	PCP	MZM Money Stock	MZMSL	Leading factor	Procyclical	MC	
	Consumer Price Index for All Urban Consumers: Transportation	CPITRNSL	Lagging factor	Procyclical	PCP						
Liquidity from	Retail Money Funds	RMFSL	Leading factor	Procyclical	FCI	Institutional Money Funds	IMFSL	Leading factor	Procyclical	FCI	2

non-banks											
Firm profitability	Corporate Profits After Tax	CP	Lagging factor	Procyclical	PCP	Corporate net cash flow	CNCF	Lagging factor	Procyclical	PCP	3
	Net corporate dividends	B056RC1A027 NBEA	Lagging factor	Procyclical	PCP						
Terms of trade	Trade Weighted U.S. Dollar Index: Broad	TWEXBMTH	Leading factor	Procyclical	FTP	Trade Weighted U.S. Dollar Index: Major Currencies	TWEXMMTH	Leading factor	Procyclical	FTP	2
Balance of payments	Net Exports of Goods and Services	NETEXP	Leading factor	Countercyclical	FTP	Real Imports of Goods & Services, 3 Decimal	IMPGSC96	Leading factor	Procyclical	FTP	3
	Real Exports of Goods & Services	EXPGSC1	Leading factor	Countercyclical	FTP						
					Micro-level conditions (29 factors)						
Labour cost/wages	Unit labor cost: nonfarm business	ULCNFB	Coincident factor	Procyclical	PCP	Business Sector: Real Output Per Hour of All Persons	OPHPBS	Coincident factor	Procyclical	PCP	5
	Nonfarm Business Sector: Real Compensation Per Hour	COMPRNFB	Coincident factor	Procyclical	PCP	Nonfarm Business Sector: Real Output Per Hour of All Persons	OPHNFB	Coincident factor	Procyclical	PCP	
	Nonfarm Business Sector: Compensation Per Hour	COMPNFB	Coincident factor	Procyclical	PCP						
Cost of capital	Effective federal funds rate	FEDFUNDS	Lagging factor	Countercyclical	MC	10-Year Treasury Constant Maturity Rate	GS10	Lagging factor	Countercyclical	MC	14
	30 year mortgage rate	MORTG	Lagging factor	Countercyclical	MC	Treasury bond yield, 10 years(Baa)	BAA10YM	Lagging factor	Countercyclical	MC	
	AAA corporate bond yield	AAA	Lagging factor	Countercyclical	MC	3-Month Treasury Bil	TB3MS	Lagging factor	Countercyclical	MC	
	BAA corporate bond yield	BAA	Lagging factor	Countercyclical	MC	10-Year Treasury Constant Maturity Minus Federal Funds Rate	T10YFF	Leading factor	Countercyclical	MC	
	Treasury bond yield, 10 years(Aaa)	AAA10YM	Lagging factor	Countercyclical	MC	Interest spead: Difference between 10-year Treasury constant maturity rate and 1-year Treasury constant maturity rate	SPREAD.GS	Leading factor	Countercyclical	MC	
	Bank prime loan rate	MPRIME	Lagging factor	Countercyclical	MC	Interest spead: Difference between 1-year BAA yield and 1-year AAA yield	SPREAD.MOODY.1	Leading factor	Countercyclical	MC	
	1-Year Treasury Constant Maturity Rate	GS1	Lagging factor	Countercyclical	MC	Interest spead: Difference between 10-year BAA yield 10-year and AAA yield	SPREAD.MOODY.2	Leading factor	Countercyclical	MC	
Cost of resources/Labour cost	PPI all commodities	PPIACO	Lagging factor	Procyclical	PCP	PPI industrial commodities	PPIIDC	Lagging factor	Procyclical	PCP	6
	PPI interm. energy goods	PPIIEG	Lagging factor	Procyclical	PCP	PPI crude energy materials	PPICEM	Lagging factor	Procyclical	PCP	
	PPI finished goods	PPIFGS	Lagging factor	Procyclical	PCP	PPI intermediate materials	PPIITM	Lagging factor	Procyclical	PCP	
Equity indexes and respective volatilities	SP500 index	SP500	Leading factor	Procyclical	PCP	Russell 2000 index	RU2000	Leading factor	Procyclical	PCP	4
	NASDAQ composite index	NASDAQ	Leading factor	Procyclical	PCP	Wilshire 5000 Total Market Full Cap Index	WILL5000	Leading factor	Procyclical	PCP	
					Total						114

Note: In the column named 8 Economic groups, (1) Money and credit is short for MC; (2) Production, income, consumption, and trade is short for PICT; (3) Federal government activities is short for FGA; (4) Inventories and inventory investment is short for INIV; (5) Fixed capital investment is short for FCI; (6) Employment and unemployment is short for EU; (7) Foreign trade and payments is short for FTP; (8) Prices, cost, and profits is short for PCP. This economic process classification method is based on Shiskin and Moore (1967). Since there is no factors in economic activity in other economy, then this study only classify all the macro factors into 8 economic groups. The definition of classification of cyclical factor is mainly based on Shiskin and Moore (1967), and *Business Cycle Indicators Handbook* published by the Conference Board gives a detailed results of classification of hundreds of macroeconomic factors. Then we use both references to classify each macro factor into 3 groups including leading, coincident, and lagging factors. In order to distinguish these factors with our constructed macro indicators, we do not call these cyclical factors, leading factors, coincident factors, and lagging factors as cyclical indicators, leading indicators, coincident indicators, and lagging indicators, respectively. The detail description of each factor available upon request.

Table 2 Classifications of macroeconomic conditions based on different groups of macro factors

Groups of macro factors (Number of factors)	Types of macroeconomic conditions
All the factors (114)	Augmented macroeconomic conditions
Factors in 6 economic groups (106)	Generalized macroeconomic conditions
Leading factors (42) Procyclical factors (86)	Incomplete macroeconomic conditions
Effective factors (29)	Specific macroeconomic conditions

Note: Both augmented macroeconomic conditions and generalized macroeconomic conditions are able to mirror comparatively complete macroeconomic conditions.

Table 3 Summary statistics

Panel A Before filtering

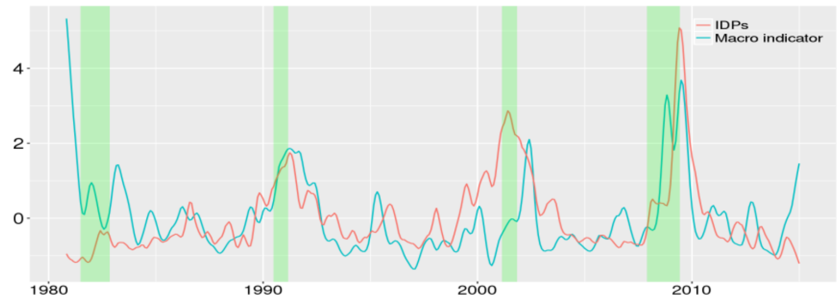
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
IDP	411	0.004	0.003	0	0.001	0.003	0.005	0.022
Defaults	411	5.445	5.685	0	2	4	7	37
Indicator.all	411	0.157	0.027	0.115	0.14	0.149	0.167	0.283
Indicator.leading	411	0.144	0.028	0.102	0.128	0.138	0.151	0.308
Indicator.procyclical	411	0.161	0.031	0.113	0.141	0.153	0.172	0.305
Indicator.6.economic	411	0.155	0.027	0.113	0.138	0.148	0.165	0.287
Indicator.effective	411	0.166	0.04	0.088	0.139	0.16	0.184	0.349

Panel B After filtering

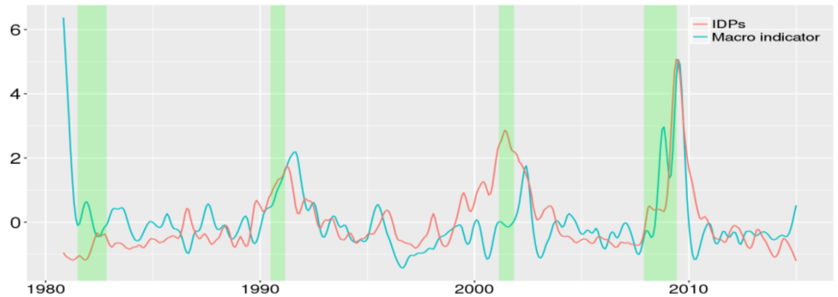
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
IDP	411	0.004	0.003	0.0001	0.002	0.002	0.005	0.018
Indicator.all	411	0.157	0.024	0.124	0.141	0.15	0.164	0.288
Indicator.leading	411	0.144	0.025	0.108	0.132	0.138	0.148	0.302
Indicator.procyclical	411	0.161	0.027	0.124	0.143	0.153	0.168	0.29
Indicator.6.economic	411	0.155	0.024	0.123	0.139	0.149	0.163	0.291
Indicator.effective	411	0.166	0.036	0.11	0.142	0.161	0.181	0.309

Figure 2 Dynamic of each macro indicator and IDP from Oct 1980 to Dec 2014 in US industrial firms and breakpoints in the time series of log-transformed IDP

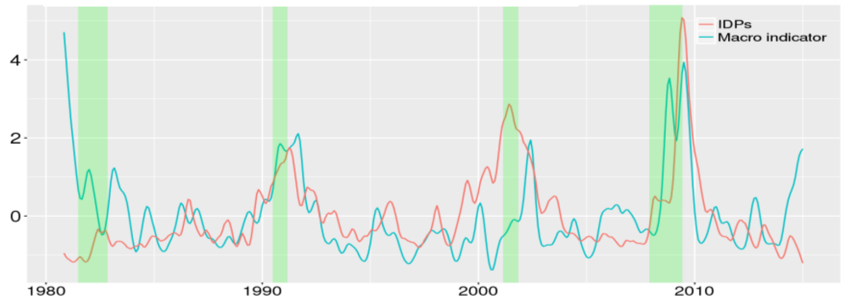
Panel A: All the factors



Panel B: Leading factors



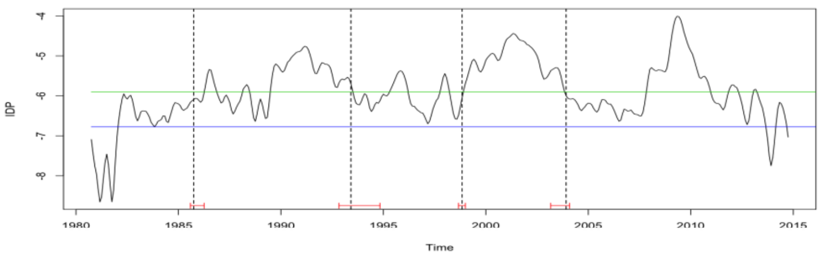
Panel C: Procyclical factors



Panel D: 6 Economic groups

Panel E: Effective factors

Panel F: Breakpoints in series of log-transformed IDP



Panel F shows the breakpoints in the time series of log-transformed IDP. This paper uses the approach proposed by Bai and Perron (2003) to determine 4 breakpoints, which are occurred in October 1985, June 1993, November 1998, December 2003. The best combination of breakpoints is identified by BIC and they are highly significant. Three points occurred after three economic recessions. The third point occurred after Asian financial crisis in 1997.

Figure 3 The percentage of defaulters located in the specific industrial groups in the industrial firms by Moody's 11 industry categories in each interval

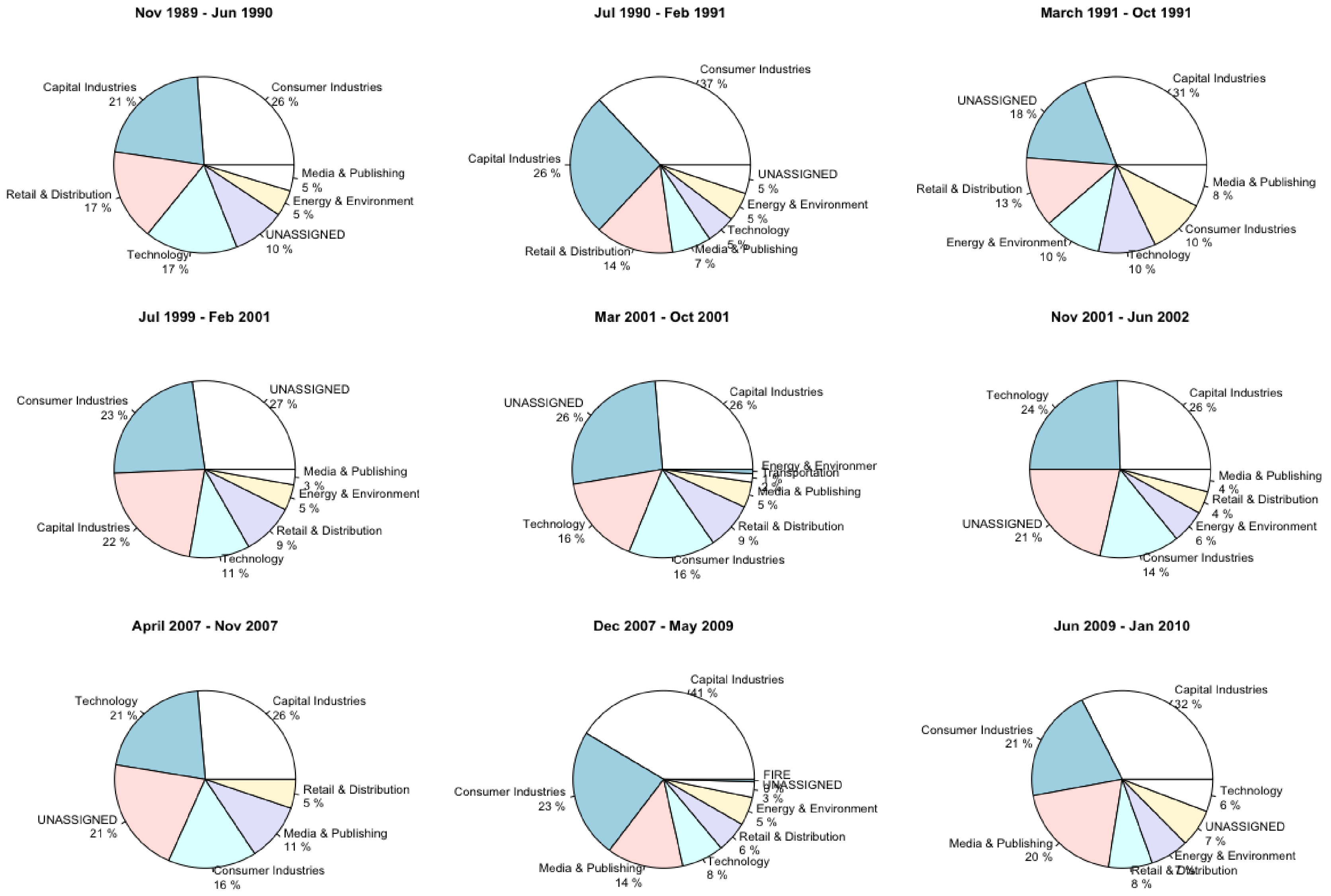


Table 4 Tests of the unit root hypothesis

	Interval	Test	Statistic	Lags	p-value
IDP	Levels				
	Interval	Test	Statistic	Lags	p-value
	1980.10-2014.12	ADF	0.3539	7	0.99
		KPSS	0.9408	4	0.01**
	1980.10-1985.10	ADF	-2.256	3	0.4713
		KPSS	1.5659	1	0.01**
	1985.11-1993.06	ADF	-1.7906	4	0.6626
		KPSS	1.3428	2	0.01**
	1993.07-1998.11	ADF	-2.8759	3	0.2199
		KPSS	0.2675	1	0.1
	1998.12-2003.12	ADF	-0.7864	3	0.9578
		KPSS	0.7142	1	0.0123**
	2004.01-2014.12	ADF	0.7326	5	0.99
		KPSS	0.7789	2	0.01**
	Differences				
	Interval	Test	Statistic	Lags	p-value
	1980.10-2014.12	ADF	-4.7317	7	0.01**
		KPSS	0.2249	4	0.1
	1980.10-1985.10	ADF	-5.1475	3	0.01**
		KPSS	0.0757	1	0.1
	1985.11-1993.06	ADF	-4.0731	4	0.01**
		KPSS	0.0737	2	0.1
	1993.07-1998.11	ADF	-3.1668	3	0.1022
		KPSS	0.0764	1	0.1
	1998.12-2003.12	ADF	-3.7363	3	0.0293**
		KPSS	0.9202	1	0.01**
	2004.01-2014.12	ADF	-0.2466	5	0.99
		KPSS	0.3476	2	0.0998*
Indicator.all	Levels				
	Interval	Test	Statistic	Lags	p-value
	1980.10-2014.12	ADF	-3.7286	7	0.0228**
		KPSS	0.4062	4	0.0745*
	1980.10-1985.10	ADF	-3.7121	3	0.0312**
		KPSS	1.5581	1	0.01**
	1985.11-1993.06	ADF	-1.1936	4	0.9033
		KPSS	0.9228	2	0.01**
	1993.07-1998.11	ADF	-2.4538	3	0.391
		KPSS	0.3472	1	0.0999*
	1998.12-2003.12	ADF	-2.5691	3	0.3446
		KPSS	0.3092	1	0.1
	2004.01-2014.12	ADF	-2.7516	5	0.2639
		KPSS	0.4496	2	0.0558*
	Differences				
	Interval	Test	Statistic	Lags	p-value
	1980.10-2014.12	ADF	-6.9981	7	0.01**
		KPSS	0.1717	4	0.1
	1980.10-1985.10	ADF	-3.5302	3	0.01**
		KPSS	0.5119	1	0.0558*
	1985.11-1993.06	ADF	-2.0548	4	0.5536
		KPSS	0.3328	2	0.1
	1993.07-1998.11	ADF	-3.9436	3	0.0179**
		KPSS	0.1153	1	0.1
	1998.12-2003.12	ADF	-2.8686	3	0.2237
		KPSS	0.1369	1	0.1
	2004.01-2014.12	ADF	-3.431	5	0.0525*
		KPSS	0.0843	2	0.1
Indicator.leading	Levels				
	Interval	Test	Statistic	Lags	p-value
	1980.10-2014.12	ADF	-4.391	7	0.01**
		KPSS	0.3067	4	0.1
	1980.10-1985.10	ADF	-4.1774	3	0.01**
		KPSS	1.0617	1	0.01**

Variable	Interval	Test	Statistic	Lags	p-value
	1985.11-1993.06	ADF	-2.1933	4	0.4966
		KPSS	1.095	2	0.01**
	1993.07-1998.11	ADF	-2.8512	3	0.2299
		KPSS	0.8933	1	0.01**
	1998.12-2003.12	ADF	-2.5872	3	0.3373
		KPSS	0.2481	1	0.1
	2004.01-2014.12	ADF	-2.6441	5	0.3087
		KPSS	0.3006	2	0.1
	Differences				
	Interval	Test	Statistic	Lags	p-value
	1980.10-2014.12	ADF	-7.3586	7	0.01**
		KPSS	0.1377	4	0.1
	1980.10-1985.10	ADF	-4.2977	3	0.01**
		KPSS	0.8113	1	0.01**
	1985.11-1993.06	ADF	-3.6288	4	0.0351**
		KPSS	0.0878	2	0.1
	1993.07-1998.11	ADF	-2.5362	3	0.3577
		KPSS	0.3238	1	0.1
	1998.12-2003.12	ADF	-3.8642	3	0.0216**
		KPSS	0.076	1	0.1
	2004.01-2014.12	ADF	-3.8813	5	0.0172**
		KPSS	0.0485	2	0.1
Indicator.procyclical	Levels				
	Interval	Test	Statistic	Lags	p-value
	1980.10-2014.12	ADF	-3.9411	7	0.0121**
		KPSS	0.3496	4	0.0989*
	1980.10-1985.10	ADF	-3.734	3	0.0294**
		KPSS	1.9031	1	0.01**
	1985.11-1993.06	ADF	-0.7346	4	0.9642
		KPSS	0.7352	2	0.0103**
	1993.07-1998.11	ADF	-2.5076	3	0.3692
		KPSS	0.2131	1	0.1
	1998.12-2003.12	ADF	-2.5522	3	0.3515
		KPSS	0.464	1	0.0498**
	2004.01-2014.12	ADF	-2.7095	5	0.2815
		KPSS	0.3266	2	0.1
	Differences				
	Interval	Test	Statistic	Lags	p-value
	1980.10-2014.12	ADF	-7.2436	7	0.01**
		KPSS	0.1487	4	0.1
	1980.10-1985.10	ADF	-3.6838	3	0.0337**
		KPSS	0.3494	1	0.099*
	1985.11-1993.06	ADF	-2.7149	4	0.2817
		KPSS	0.2462	2	0.1
	1993.07-1998.11	ADF	-2.9753	3	0.1798
		KPSS	0.1776	1	0.1
	1998.12-2003.12	ADF	-2.7582	3	0.2683
		KPSS	0.1314	1	0.1
	2004.01-2014.12	ADF	-3.7368	5	0.0243**
		KPSS	0.0802	2	0.1
Indicator.6.economic.groups	Levels				
	Interval	Test	Statistic	Lags	p-value
	1980.10-2014.12	ADF	-3.7586	7	0.0212**
		KPSS	0.496	4	0.0426**
	1980.10-1985.10	ADF	-3.974	3	0.0168**
		KPSS	1.6248	1	0.01**
	1985.11-1993.06	ADF	-1.142	4	0.9113
		KPSS	0.6643	2	0.0168**
	1993.07-1998.11	ADF	-2.5734	3	0.3425
		KPSS	0.4414	1	0.0593*
	1998.12-2003.12	ADF	-2.7398	3	0.2756
		KPSS	0.3064	1	0.1
	2004.01-2014.12	ADF	-2.6956	5	0.2872
		KPSS	0.4817	2	0.0458**

	Differences				
	Interval	Test	Statistic	Lags	*p*-value
	1980.10-2014.12	ADF	-7.1747	7	0.01**
		KPSS	0.1692	4	0.1
	1980.10-1985.10	ADF	-3.369	3	0.2794
		KPSS	0.5463	1	0.0509*
	1985.11-1993.06	ADF	-2.144	4	0.5169
		KPSS	0.2826	2	0.1
	1993.07-1998.11	ADF	-4.1247	3	0.01**
		KPSS	0.1416	1	0.1
	1998.12-2003.12	ADF	-2.7392	3	0.276
		KPSS	0.1435	1	0.1
	2004.01-2014.12	ADF	-3.6574	5	0.0308**
		KPSS	0.0788	2	0.1
Indicator.effective	Levels				
	Interval	Test	Statistic	Lags	*p*-value
	1980.10-2014.12	ADF	-3.6079	7	0.0323**
		KPSS	0.6294	4	0.02**
	1980.10-1985.10	ADF	-3.2178	3	0.0931*
		KPSS	0.2192	1	0.1
	1985.11-1993.06	ADF	-2.3119	4	0.4477
		KPSS	0.2532	2	0.1
	1993.07-1998.11	ADF	-3.4834	3	0.0504*
		KPSS	0.4469	1	0.057*
	1998.12-2003.12	ADF	-3.2548	3	0.0872*
		KPSS	0.5009	1	0.0415**
	2004.01-2014.12	ADF	-2.1204	5	0.5264
		KPSS	0.6058	2	0.0221**
	Differences				
	Interval	Test	Statistic	Lags	*p*-value
	1980.10-2014.12	ADF	-7.6945	7	0.01**
		KPSS	0.052	4	0.1
	1980.10-1985.10	ADF	-3.3966	3	0.0649*
		KPSS	0.3163	1	0.1
	1985.11-1993.06	ADF	-3.209	4	0.0913*
		KPSS	0.1934	2	0.1
	1993.07-1998.11	ADF	-3.9713	3	0.0166**
		KPSS	0.1027	1	0.1
	1998.12-2003.12	ADF	-3.7168	3	0.031**
		KPSS	0.0672	1	0.1
	2004.01-2014.12	ADF	-3.9688	5	0.013**
		KPSS	0.061	2	0.1

Table 5 Confirmatory Analysis

Interval	IDP	Indicator (All factors)		Indicator (Leading factors)		Indicator (Procyclical factors)		Indicator (6 Economic groups)		Indicator (Effective factors)	
	I(m)	I(m)	Types of tests	I(m)	Types of tests	I(m)	Types of tests	I(m)	Types of tests	I(m)	Types of tests
1980.10-2014.12	I(1)	I(0)		I(0)		I(0)		I(1)	CT	I(1)	CT
1980.10-1985.10	I(1)	I(4)		**I(1)**	CT	I(1)	CT	I(7)		I(0)	
1985.11-1993.06	I(1)	I(1)	CT	I(1)	CT	I(1)	CT	I(1)	CT	I(0)	
1993.07-1998.11	I(0)	I(0)	GCT	I(1)		I(0)	GCT	I(0)	GCT	I(0)	GCT
1998.12-2003.12	**I(1)**	I(0)		I(0)		I(1)	CT	I(0)		I(1)	CT
2004.01-2014.12	I(1)	I(0)		I(0)		I(0)		I(1)	CT	I(1)	CT

Note: I(m) means that the variable converts to stationarity after being integrated of the order m. The bold type I(1) means that after using various order for integration in the variables, these variables still do not pass the stationary test based on KPSS. However, they pass the ADF test after first order integration. Although this study uses KPSS test as the standard for deciding the order of m, for this case, the ADF test is used. Therefore, the cointegration test is used for cross checking whether they are cointegrated with the other variables.

Two abbreviations in the column titled Types of tests are CT and GCT, which represent cointegration test and Granger causality test, respectively. If both two variables are stationary, then Granger causality is used for testing the causality relationship between two variables (Lütkepohl, 2005). For the other cases, Toda and Yamamoto causality test is used for checking causality in the nonstationary variables (Pfaff, 2008).

Table 6 Diagnostics tests for VAR (p) specification between each indicator and IDP

Panel A Macro indicator constructed by all the factors

Interval	Obs	Lag	Serial correlation		ARCH effect test		Jarque-Bera normality tests	
			Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value
1980.10-2014.12	411	7	50.012	0.06034	60.729	0.05878*	65238	< 2.2e-16***
1980.10-1985.10	61	3	44.763	0.7515	42.178	0.5922	4.847	0.3034
1985.11-1993.06	92	4	53.411	0.2742	37.025	0.7952	5.8426	0.2112
1993.07-1998.11	65	4	36.762	0.8813	50.344	0.2702	4.168	0.3837
1998.12-2003.12	61	3	68.143	0.06584	46.791	0.3988	2.7853	0.5944
2004.01-2014.12	132	4	54.624	0.2374	27.784	0.9795	3894.3	< 2.2e-16***

Panel B Macro indicator constructed by leading factors

Interval	Obs	Lag	Serial correlation		ARCH effect test		Jarque-Bera normality tests	
			Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value
1980.10-2014.12	411	4	43.201	0.6695	69.851	0.01023**	65370	< 2.2e-16***
1980.10-1985.10	61	4	36.766	0.8812	33.088	0.9058	9.2625	0.05486
1985.11-1993.06	92	4	39.398	0.8071	47.388	0.3755	1.2417	0.8712
1993.07-1998.11	65	4	56.568	0.1855	39.142	0.7175	1.3722	0.849
1998.12-2003.12	61	3	55.27	0.3522	47.769	0.3609	0.57933	0.9653
2004.01-2014.12	132	4	34.872	0.9217	28.895	0.9702	5173.1	< 2.2e-16***

Panel C Macro indicator constructed by procyclical factors

Interval	Obs	Lag	Serial correlation		ARCH effect test		Jarque-Bera normality tests	
			Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value
1980.10-2014.12	411	4	56.683	0.1828	97.352	0.00001006***	64579	< 2.2e-16***
1980.10-1985.10	61	3	65.46	0.09944	56.424	0.1182	9.591	0.04791
1985.11-1993.06	92	4	40.11	0.7838	53.345	0.1841	2.0882	0.7195
1993.07-1998.11	65	4	49.745	0.4036	48.483	0.3343	0.4097	0.4097
1998.12-2003.12	61	3	65.237	0.1028	40.122	0.6783	1.4984	0.8269
2004.01-2014.12	132	4	49.175	0.4258	26.644	0.9866	4481.5	< 2.2e-16***

Panel D Macro indicator constructed by the factors in the 6 economic groups

Interval	Obs	Lag	Serial correlation		ARCH effect test		Jarque-Bera normality tests	
			Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value
1980.10-2014.12	411	4	61.186	0.0958	70.203	0.009494***	64811	< 2.2e-16***
1980.10-1985.10	61	4	39.601	0.8006	48.009	0.3518	9.3042	0.05393
1985.11-1993.06	92	4	37.126	0.8723	57.022	0.1078	1.8394	0.7653
1993.07-1998.11	65	4	45.304	0.584	37.202	0.7892	2.3946	0.6636
1998.12-2003.12	61	4	47.61	0.4887	39.061	0.7206	2.463	0.6513
2004.01-2014.12	132	4	41.487	0.4107	37.725	0.7707	5681.7	< 2.2e-16***

Panel E Macro indicator constructed by the effective factors extracted by Lasso

Interval	Obs	Lag	Serial correlation		ARCH effect test		Jarque-Bera normality tests	
			Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value
1980.10-2014.12	411	5	51.003	0.2175	63.257	0.03748**	85076	< 2.2e-16***
1980.10-1985.10	61	4	39.601	0.8006	48.009	0.3518	9.3042	0.05393
1985.11-1993.06	92	4	37.126	0.8723	57.022	0.1078	1.8394	0.7653
1993.07-1998.11	65	4	45.304	0.584	37.202	0.7892	2.3946	0.6636
1998.12-2003.12	61	4	47.61	0.4887	39.061	0.7206	2.463	0.6513
2004.01-2014.12	132	4	41.487	0.4107	37.725	0.7707	5681.7	< 2.2e-16***

Table 7 Johansen's cointegration tests between each macro indicator and IDPs

This table provides the cointegration results after using Johansen's test in 6 samples including total sample, sample from October 1980 to October 1985, sample from November 1985 to June 1993, sample from July 1993 to November 1998, sample from December 1998 to December 2003, and sample from January 2004 to December 2014. Panel A reports the results from using eigenvalue test between each indicator and IDP in different samples. Panel B reports the results from using trace test in different samples. $r = 0$, there is no cointegrated vectors. $r <= 1$, there is 1 integrated vector. FH means that the test fail to reject $r = 0$ or $r <= 1$. Significant at the ***1% level, the ** 5% level and the * 10% level.

Panel A Eigenvalue Test

Interval		Values of test statistic/Decision										Critical values of test		
		Indicator (All factors)		Indicator (Leading factors)		Indicator (Procyclical factors)		Indicator (6 Economic groups)		Indicator (Effective factors)		10%	5%	1%
1980.10-2014.12	$r <= 1$							**1.48**	**FH**	3.21	**FH**	7.52	9.24	12.97
	$r = 0$							**27.27**	**RH**	20.27	**RH**	13.75	15.67	20.2
1980.10-1985.10	$r <= 1$			10.52	RH	9.71	RH	9.51	FH			7.52	9.24	12.97
	$r = 0$			28.87	RH	12.02	FH	20.04	RH			13.75	15.67	20.2
1985.11-1993.06	$r <= 1$	2.43	FH	2	FH	2.03	FH	2.84	FH			7.52	9.24	12.97
	$r = 0$	8.9	FH	11.07	FH	8.51	FH	8.37	FH			13.75	15.67	20.2
1993.07-1998.11	$r <= 1$											7.52	9.24	12.97
	$r = 0$											13.75	15.67	20.2
1998.12-2003.12	$r <= 1$					1.59	FH			**0.9**	**FH**	7.52	9.24	12.97
	$r = 0$					9.78	FH			**21.69**	**RH**	13.75	15.67	20.2
2004.01-2014.12	$r <= 1$					3.82	FH	3.43	FH	2.35	FH	7.52	9.24	12.97
	$r = 0$					18.98	FH	15.66	FH	9.91	FH	13.75	15.67	20.2

Panel B Trace Test

Interval		Values of test statistic										Critical values of test		
		Indicator (All factors)		Indicator (Leading factors)		Indicator (Procyclical factors)		Indicator (6 Economic groups)		Indicator (Effective factors)		10%	5%	1%
1980.10-2014.12	$r <= 1$							**1.48**	**FH**	3.21	**FH**	7.52	9.24	12.97
	$r = 0$							**28.75**	**RH**	23.47	**RH**	17.85	19.96	24.6
1980.10-1985.10	$r <= 1$			10.52	RH	9.71	RH	9.51	RH			7.52	9.24	12.97
	$r = 0$			39.39	RH	21.73	FH	29.55	RH			17.85	19.96	24.6
1985.11-1993.06	$r <= 1$	2.43	FH	2	FH	2.03	FH	2.84	FH			7.52	9.24	12.97
	$r = 0$	11.34	FH	13.07	FH	10.54	FH	11.21	FH			17.85	19.96	24.6
1993.07-1998.11	$r <= 1$											7.52	9.24	12.97
	$r = 0$											17.85	19.96	24.6
1998.12-2003.12	$r <= 1$					1.59	FH			**0.9**	**FH**	7.52	9.24	12.97
	$r = 0$					11.36	FH			**22.59**	**RH**	17.85	19.96	24.6
2004.01-2014.12	$r <= 1$					3.82	FH	3.43	FH	2.35	FH	7.52	9.24	12.97
	$r = 0$					22.8	FH	19.09	FH	12.26	FH	17.85	19.96	24.6

Table 8 Causality analysis

This table shows results of investigation of the causal relationship between IDP and macro indicators in 6 samples including total sample, sample from October 1980 to October 1985, sample from November 1985 to June 1993, sample from July 1993 to November 1998, sample from December 1998 to December 2003, sample from January 2004 to December 2014. The results of max order integration ($\boldsymbol{m}$) is from Table 5 and the results of lag in VAR ($\boldsymbol{p}$) is from Table 6. Following the results from Table 4, all the indicators except the indicator constructed by leading factors in the fourth interval and IDP are stationary in the levels I(0). Then their relationships are tested by Granger causality. For the other cases, this study uses TY causality test proposed by Toda and Yamamoto (1995) for investigating the relationship between each indicator and IDP. Shadow area means that there is cointegration between IDP and macro indicator. Significant at the ***1% level, the ** 5% level and the * 10% level.

Panel A Macro indicator constructed by all the factors

	H_0: Indicator does not Granger-cause IDP		H_0: IDP does not Granger-cause Indicator		Max order integration	Lag in VAR
Interval	Test Statistic	P-value	Test Statistic	P-value	(m)	(p)
1980.10-2014.12	3.4	0.84	10.6	0.16	1	7
1980.10-1985.10	4.7	0.19	**14.5**	**0.0023****	4	3
1985.11-1993.06	4.3	0.37	**8.7**	**0.07****	1	4
1993.07-1998.11	**3.8371**	**0.0083*****	1.18	0.3305	1	4
1998.12-2003.12	3.3	0.34	1.7	0.63	1	3
2004.01-2014.12	**2.4693**	**0.0484****	0.4466	0.7747	1	4

Panel B Macro indicator constructed by leading factors

	H_0: Indicator does not Granger-cause IDP		H_0: IDP does not Granger-cause Indicator		Max order integration	Lag in VAR
Interval	Test Statistic	P-value	Test Statistic	P-value	(m)	(p)
1980.10-2014.12	1.1	0.9	3.9	0.42	1	4
1980.10-1985.10	**17**	**0.0022*****	3.4	0.5	1	4
1985.11-1993.06	0.94	0.92	**8.2**	**0.086****	1	4
1993.07-1998.11	1.9	0.76	0.65	0.96	1	4
1998.12-2003.12	4.1	0.25	1.9	0.59	1	3
2004.01-2014.12	4	0.41	3.6	0.46	1	4

Panel C Macro indicator constructed by procyclical factors

	H_0: Indicator does not Granger-cause IDP		H_0: IDP does not Granger-cause Indicator		Max order integration	Lag in VAR
Interval	Test Statistic	P-value	Test Statistic	P-value	(m)	(p)
1980.10-2014.12	1.2	0.88	5.9	0.21	1	4
1980.10-1985.10	**7**	**0.07***	5.1	0.16	1	3
1985.11-1993.06	3.8	0.43	5.8	0.22	1	4
1993.07-1998.11	**2.4657**	**0.0563***	**4.6389**	**0.0028*****	1	4
1998.12-2003.12	3.8	0.44	2.2	0.54	1	3
2004.01-2014.12	3.8	0.43	2.7	0.61	1	4

Panel D Macro indicator constructed by the factors in the 6 economic groups

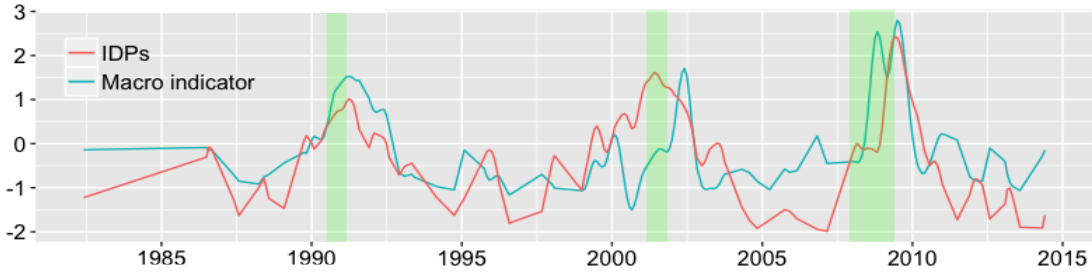
	H_0: Indicator does not Granger-cause IDP		H_0: IDP does not Granger-cause Indicator		Max order integration	Lag in VAR
Interval	Test Statistic	P-value	Test Statistic	P-value	(m)	(p)
1980.10-2014.12	0.41	0.98	**8.2**	**0.085***	1	4
1980.10-1985.10	2.1	0.56	**12.8**	**0.0051***	7	3
1985.11-1993.06	3.4	0.49	**8.8**	**0.066***	1	4
1993.07-1998.11	**2.764**	**0.037****	1.4467	0.2319	1	4
1998.12-2003.12	4.4	0.22	2.7	0.43	1	3
2004.01-2014.12	**1.9866**	**0.10**	0.3388	0.8513	1	4

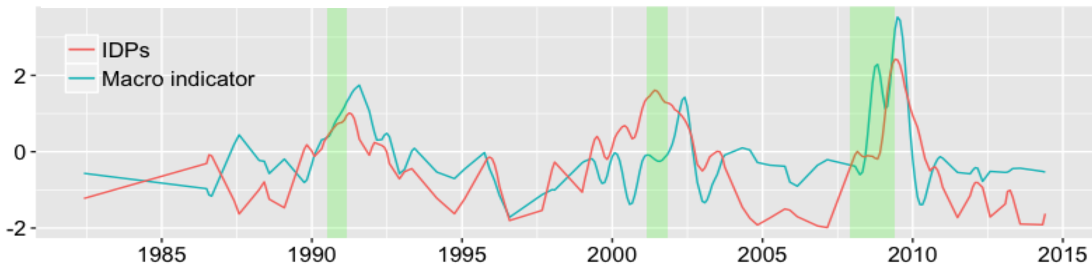
Panel E Macro indicator constructed by the effective factors extracted by Lasso

	H_0: Indicator does not Granger-cause IDP		H_0: IDP does not Granger-cause Indicator		Max order integration	Lag in VAR
Interval	Test Statistic	P-value	Test Statistic	P-value	(m)	(p)
1980.10-2014.12	**11.2**	**0.048****	3.1	0.68	1	5
1980.10-1985.10	**8.9**	**0.063***	5.5	0.24	1	4
1985.11-1993.06	2.3	0.68	2.3	0.68	1	4
1993.07-1998.11	**3.8245**	**0.0085*****	2.0	0.5752	1	4
1998.12-2003.12	3.2	0.52	2	0.74	1	4
2004.01-2014.12	4	0.41	4.9	0.3	1	4

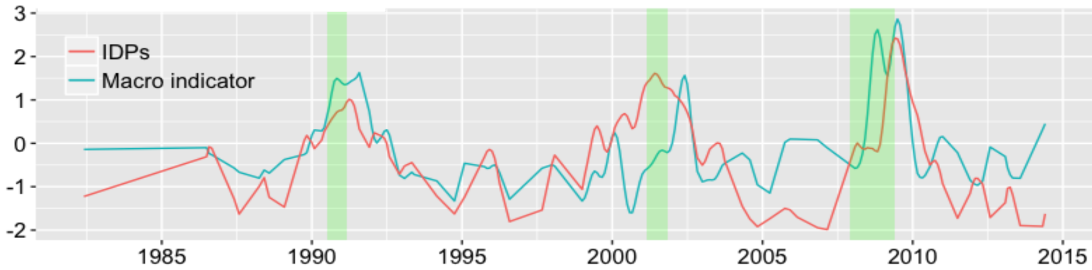
Figure 4 Dynamic of macro indicator and IDP after removing the monthly defaults < 5. There is no lag for each variable.

Panel A: All the factors

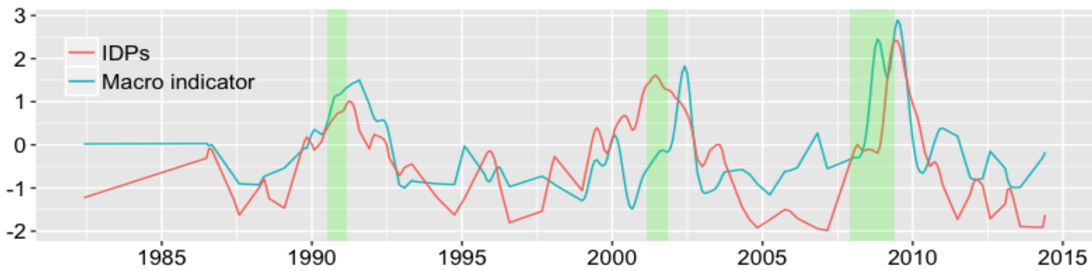




Panel C: Procyclical factors



Panel D: 6 Economic groups



Panel E: Effective factors

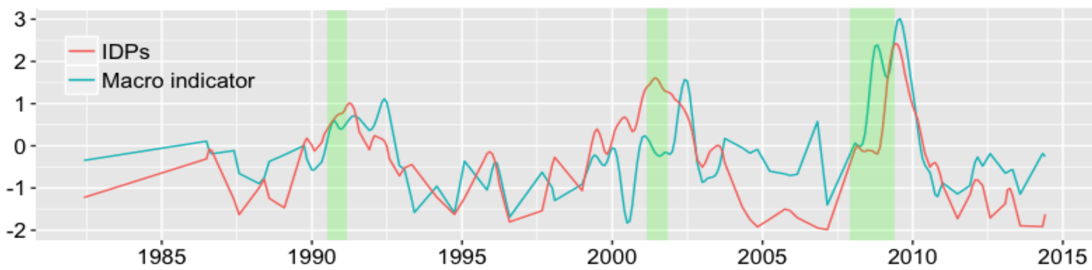


Table 9 Regression results without any lags

Panel A reports the regression results. The regression is defined as $Y_t = \beta_0 + \beta_1 X_t + \beta_2 D_t + \beta_3 X_t D_t + \varepsilon$, where Y_t is the dependent variable IDP at date t, and X_t is independent variable (5 macro indicators) at date t. D_t is the dummy variable, 1 means recession; 0 means no recession. The macro indicators in the column from (1) to (5) are constructed by five groups of factors, which are all the factors, leading factors, procyclical factors, factors in the 6 economic groups, and effective factors, respectively. Panel B reports the mean default risk (IDP) function in nonrecession period. The function is written as $E(Y_t|D_t = 0, X_t) = \beta_0 + \beta_1 X_t$. Panel C reports the mean default risk (IDP) function in recession period. The function is defined as $E(Y_t|D_t = 1, X_t) = (\beta_0 + \beta_2) + (\beta_1 + \beta_3)X_t$, where $\beta_0 + \beta_2$ is the new constant and $\beta_1 + \beta_3$ is the new coefficient for indicator, X_t. Both IDP and each indicator are standardised. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. Standard errors are reported in parentheses underneath the coefficients.

Panel A: Regression results

	Dependent variable: IDP				
	(1) All the factors	(2) Leading factors	(3) Procyclical factors	(4) 6 Economic groups	(5) Effective factors
Indicator	0.616***	0.537***	0.558***	0.597***	0.620***
	-0.079	-0.078	-0.086	-0.079	-0.074
Recession	0.732***	0.689***	0.752***	0.737***	0.751***
	-0.193	-0.187	-0.2	-0.194	-0.187
Indicator *Recession	-0.563***	-0.363**	-0.522***	-0.541***	-0.570***
	-0.157	-0.16	-0.158	-0.161	-0.161
Constant	-0.051	-0.087	-0.059	-0.058	-0.064
	-0.071	-0.072	-0.075	-0.071	-0.069
Observations	169	169	169	169	169
R2	0.365	0.331	0.31	0.358	0.394
Adjusted R2	0.354	0.319	0.297	0.346	0.383
Residual Std. Error	0.804 (df = 165)	0.825 (df = 165)	0.838 (df = 165)	0.808 (df = 165)	0.786 (df = 165)
F Statistic	31.658*** (df = 3; 165)	27.226*** (df = 3; 165)	24.674*** (df = 3; 165)	30.679*** (df = 3; 165)	35.725*** (df = 3; 165)

Panel B: Mean default risk (IDP) function for non-recession

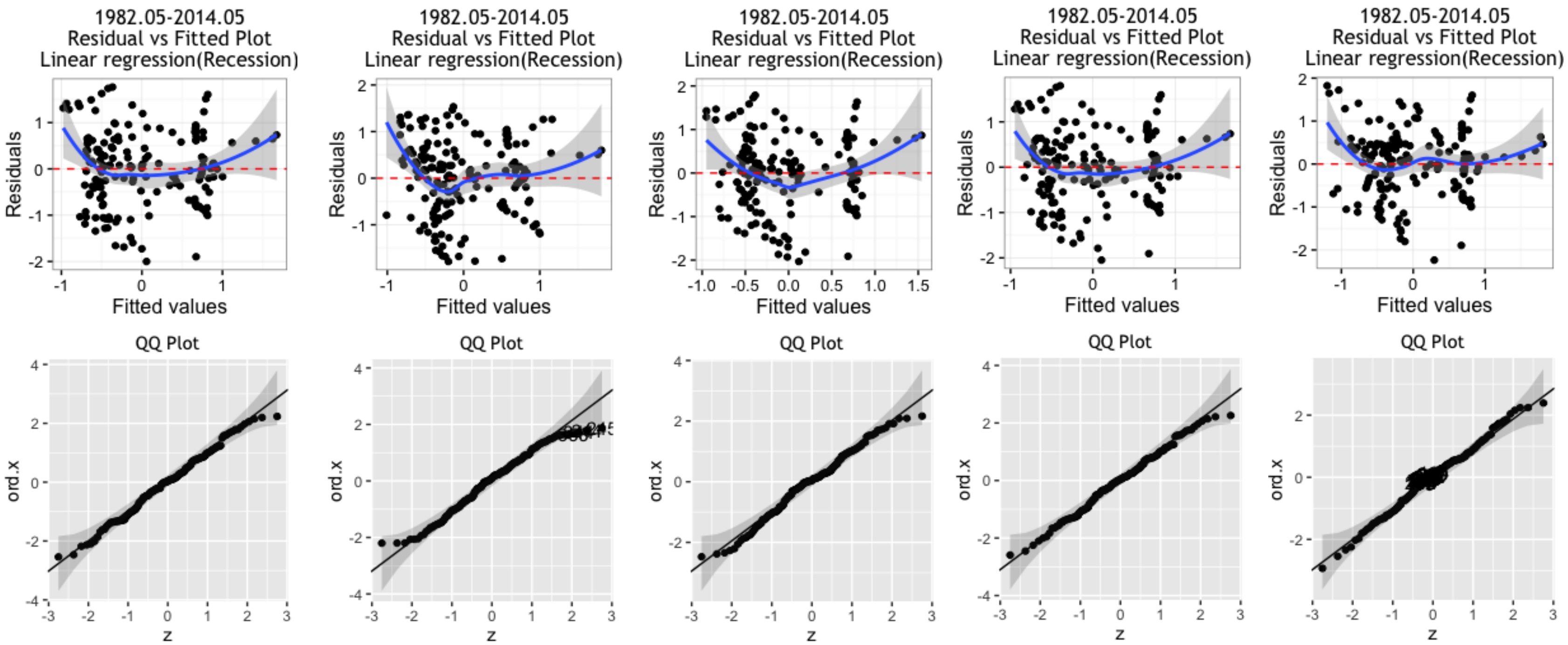
Indicator	0.616	0.537	0.558	0.597	0.62
Constant	-0.051	-0.087	-0.059	-0.058	-0.064

Panel C: Mean default risk (IDP) function for recession

Indicator	0.053	0.174	0.036	0.056	0.05
Constant	0.681	0.602	0.693	0.679	0.687

Figure 5 Model diagnostics for the models in Table 9

Panel A1: All the factors | Panel A2: Leading factors | Panel A3: Procyclical factors | Panel A4: 6 Economic groups | Panel A5: Effective factors



Panel B: Results of Heteroscedasticity tests

Types of indicator	Statistic	P.value
(1) All the factors	1.8876	0.1695
(2) Leading factors	1.3029	0.2537
(3) Procyclical factors	0.5499	0.4584
(4) 6 Economic groups	1.6843	0.1944
(5) Effective factors	1.5838	0.2082

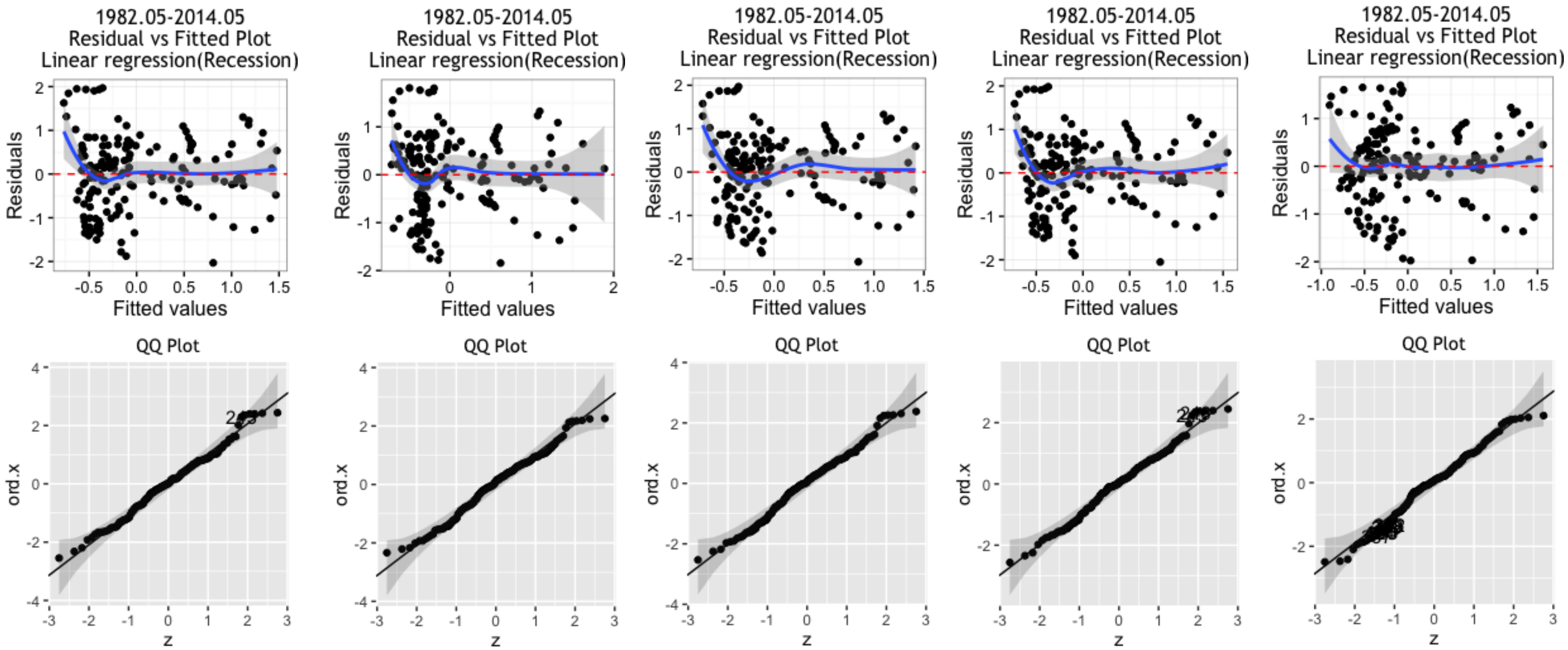
Table 10 Regression results after lagging indicator and recession

Panel A reports the regression results. The regression is defined as $Y_t = \beta_0 + \beta_1 X_{t-3} + \beta_2 D_{t-3} + \beta_3 X_{t-3} D_{t-3} + \varepsilon$, where Y_t is the dependent variable IDP at date $t-3$, and X_{t-3} is independent variable (5 macro indicators) at date $t-3$. D_t is the dummy variable, 1 means recession; 0 means no recession. The macro indicators in the column from (1) to (5) are constructed by five groups of factors, which are all the factors, leading factors, procyclical factors, factors in the 6 economic groups, and effective factors, respectively. Panel B reports the mean default risk (IDP) function in nonrecession period. The function is written as $E(Y_t|D_{t-3} = 0, X_{t-3}) = \beta_0 + \beta_1 X_{t-3}$. Panel C reports the mean default risk (IDP) function in recession period. The function is defined as $E(Y_t|D_{t-3} = 1, X_{t-3}) = (\beta_0 + \beta_2) + (\beta_1 + \beta_3)X_{t-3}$, where $\beta_0 + \beta_2$ is the new constant and $\beta_1 + \beta_3$ is the new coefficient for indicator, X_{t-3}. Both IDP and each indicator are standardised. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. Standard errors are reported in parentheses underneath the coefficients.

Panel A: Regression results					
	Dependent variable: IDP				
	(1) All the factors	(2) Leading factors	(3) Procyclical factors	(4) 6 Economic groups	(5) Effective factors
Indicator	0.404***	0.388***	0.354***	0.386***	0.403***
	-0.083	-0.079	-0.088	-0.081	-0.077
Recession	0.775***	0.791***	0.808***	0.769***	0.797***
	-0.195	-0.183	-0.198	-0.196	-0.193
Indicator *Recession	-0.08	-0.006	-0.073	-0.044	-0.06
	-0.158	-0.156	-0.158	-0.162	-0.168
Constant	-0.146**	-0.163**	-0.154**	-0.152**	-0.156**
	-0.073	-0.072	-0.076	-0.074	-0.072
Observations	169	169	169	169	169
R2	0.334	0.343	0.302	0.329	0.344
Adjusted R2	0.321	0.331	0.29	0.317	0.332
Residual Std. Error	0.824 (df = 165)	0.818 (df = 165)	0.843 (df = 165)	0.826 (df = 165)	0.818 (df = 165)
F Statistic	27.532*** (df = 3; 165)	28.729*** (df = 3; 165)	23.843*** (df = 3; 165)	26.992*** (df = 3; 165)	28.793*** (df = 3; 165)
Panel B: Mean default risk (IDP) function for non-recession					
Indicator	0.404	0.388	0.354	0.386	0.403
Constant	-0.146	-0.163	-0.154	-0.152	-0.156
Panel C: Mean default risk (IDP) function for recession					
Indicator	0.324	0.382	0.281	0.342	0.343
Constant	0.629	0.628	0.654	0.617	0.641

Figure 6 Model diagnostics for the models in Table 10

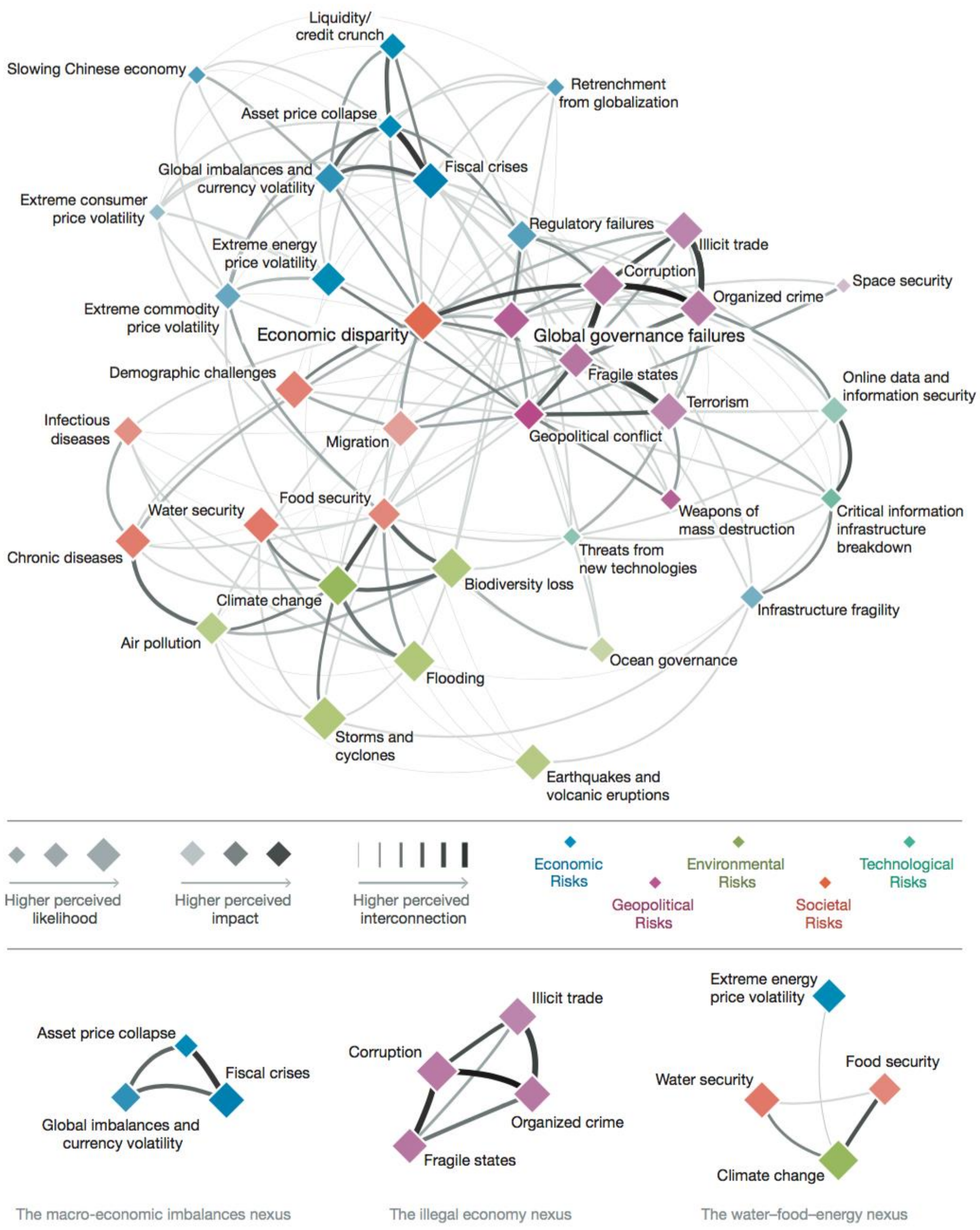
Panel A1: All the factors | Panel A2: Leading factors | Panel A3: Procyclical factors | Panel A4: 6 Economic groups | Panel A5: Effective factors



Panel B: Results of Heteroscedasticity tests

Types of indicator	Statistic	P.value
(1) All the factors	2.7578	0.0968
(2) Leading factors	1.7793	0.1822
(3) Procyclical factors	1.1134	0.2914
(4) 6 Economic groups	2.5978	0.107
(5) Effective factors	0.2486	0.618

Figure 7 Risks Interconnection Map 2011 illustrating systemic interdependencies in the hyper-connected world we are living in.



Source: this figure is taken from Helbing (2013)