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IMPORTANCE In early 2020, the global COVID-19 pandemic interrupted a decade-long US expansionary cycle. Equity markets plummeted, but quickly recovered and moved back to positive territory in only a few months. Could the quick recovery have been predicted? We believe we are the first to investigate a new variable that might have provided an early indication that the market had over-reacted to the COVID-19 pandemic based on S&P Credit Watch activity. We further examine this variable's explanatory power when applied to both the life/health and property/casualty insurance industries, and find its power diminished. We surmise this is due to the industry's known resilience and/or higher level of disclosure requirements.

OBJECTIVES

1. Test the validity and explanatory power of a new variable associated with GDP to see if it could have provided an early indication of market over-reaction;
2. Apply the new variable to the more-insulated and highly-regulated insurance industry and note any change in its explanatory power.

RELEVANCE Previous literature has established that credit rating agencies reduce the information gap between corporations and investors, due to access to private information resulting from credit rating agencies' exemption from Regulation FD. Focusing on the S&P Credit Watch activity, which is intended to signal potential upcoming ratings changes due to new and often private information, we find that this variable was closely associated with GDP both during and following the two previous recessions. However, when applied to the recession associated with COVID-19, we find that it was correlated with a smaller GDP loss than what was actually experienced, leading us to wonder if those monitoring Credit Watch activity could have anticipated a recovery, since the variable during that time was not as strongly negatively associated with the market's ultimate reaction.

We further investigate the explanatory power of this variable by applying it separately to the life/health and property/casualty insurance industries where there is less private information for credit rating agencies to discover, due to significantly heightened regulatory requirements. In addition, previous literature has also shown that the insurance industry is less susceptible to systemic risk. With less private information to discover and an industry more insulated from economic shock, one

might expect the Credit Watch activity variable to have less explanatory power than it does when applied to other industries, and indeed, that is what we find.

More research is needed to establish the ultimate predictive value of the S&P Credit Watch activity variable. Our sample spans 25 years, and includes 68,167 Credit Watch actions, with 53,001 Credit Watch Negative warnings and 15,166 Credit Watch Positive alerts. We create a variable comparing the positive and negative Credit Watch alerts in ratio form, pooling them by calendar quarters, and include the variable into a model examining other economic factors known to be associated with GDP. We discover this variable's validitye and can show it has explanatory power in our model; however, this period of time includes only 3 recessions, which presents an obstacle to claiming predictive value. Further, our research establishes that the variable's power is diminished when applied to the insurance industry.

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ABSTRACT

A global pandemic interrupted a decade-long US expansionary cycle. While governments intervened in an attempt to manage a health crisis, the economy stalled, and equity markets crashed. However, equity markets quickly recovered and moved to positive territory a few months later. We examine the actions of Credit Rating Agencies (CRAs) and the signals that are sent through S&P Watch List activity. After creating a significant indicator based on Credit Watch activity, reflecting private firm information, we find that the swift recovery may have been foreseeable for non-insurance firms. The indicator provides less potential predictive power for insurance firms, either because the greater regulatory activity surrounding insurance firms yields less private information to be discovered by CRAs, or possibly because the insurance industry is more resilient to economic shock than other sectors of the economy.

JEL Classification: E32, D82, G24

Keywords: Credit ratings, Economic Indicators, COVID-19

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1. Introduction

A global pandemic ended a decade-long period of economic expansion in the U.S. As local governments took action to restrict business and consumer activity, production stalled and gross domestic product (GDP) plunged. The World Health Organization (WHO) declared COVID-19 a pandemic at the end of the first quarter of 2020, and GDP numbers in the second quarter were abysmal. While the first quarter's GDP approached 0%, the second quarter saw a decrease of over 9% according to the U.S. Department of Commerce (DOC). Economic indicators portended an economic collapse, and equity markets suffered accordingly.

However, U.S. equity markets quickly recovered losses, and by the end of the second quarter, they moved into positive territory for the year, despite having lost over one-third of their value in the first quarter. The goal of this paper is to analyze the association of CRA actions with GDP during times of economic contraction and assess whether CRA Watch activity might provide information about future GDP recovery. Further, if there is useful information provided by CRA Watch activity, we will investigate if that value persists in the highly regulated insurance industry, which would potentially have less private information available to incorporate into CRA ratings. If so, this would tend to indicate that there is either less private information to discover in the insurance industry, or the insurance industry is more resilient to economic shocks than other sectors.

The primary role of CRAs is to reduce the information gap that exists between borrowers and investors, quantifying the ability of an entity to meet its financial obligations. Additionally, credit ratings are mandated for banks, many pension funds, and mutual funds. Credit ratings are also assigned automatically to all corporate debt issues exceeding $100 million. These CRA actions are based on private firm information, which is revealed as discussed later in the paper. While the government's restrictive actions were unprecedented in modern times, we examine whether the indicators revealed any information that could have guided economic expectations and, in turn, equity investors. To do so, we compare CRA CreditWatch actions at the time COVID-19 was unfolding with past economic contractions. Auh (2015) shows that firm ratings are overly optimistic during expansionary economic cycles. Conversely, when the economy slows, firm ratings decline more than fundamentals might suggest. Auh (2015) rationalizes that firm failures are more common during economic downturns, and CRAs adjust their ratings to reflect this increased risk of default. It then follows that CRA adjustments might provide a reasonable proxy for expected firm failures related to economic contraction. Our results show that an indicator based on a CreditWatch List did not react as strongly as predicted by past economic contractions. Specifically, our indicator suggested an economic contraction of approximately -4.25%. While the market reacted to the larger, actual GDP contraction, we suggest that the equity market recovery may have been anticipated based on an examination of CRA activities.

To further bolster our contention that the potential predictive power of the CreditWatch actions is based on the discovery of private information, we examine the highly regulated insurance sector as a subsample. Insurers must reveal a great deal of additional financial information to state insurance regulators, which means there is less private information for CRAs to discover, ultimately weakening the potential predictive power of the CreditWatch actions for insurers. It is also possible that the insurance industry is more resilient to economic downturns than other industries, which would also indicate the weakened power of the CreditWatch actions when applied to insurers. When applied to insurers, we find statistical, but not economic, significance attached to our CreditWatch indicator.

2. Literature Review

Government interventions restricting household and business activity were meant to reduce negative health outcomes associated with the COVID-19 virus. The restrictions were intended to be short-term while the medical community assessed the virus and worked on managing illness and finding a cure. Therefore, original expectations should have been in line with an economic pause rather than a long-term economic recession. However, the sharp decline in equities suggested that investors expected a sustained economic contraction. If the economy was simply pausing, forward-looking equity markets should not have dropped as precipitously as they did.

We investigate the relationship between CRA activity and economic activity by examining CreditWatch actions. The ratings literature is vast in showing that CRAs rate cyclically (Frydman & Schuermann, 2008; Figlewski et al., 2012; Dang & Partington, 2014). Also, Boot et al. (2006) discuss the important economic role CRAs play, as credit ratings provide a "focal point" for multiple stakeholders in a complex financial world with multiple factors. It is also important to understand the rating process, specifically as it applies to CreditWatch actions. CRAs interact regularly with firms and collect private information. Firm management is interested in providing information to CRAs and receiving a rating because the presence of a credit rating attracts institutional investors and increases overall capital market interest. When a CRA believes there is better than a 50% chance that a rating will change within the next 90 days, a CreditWatch warning is communicated. These warnings can be either positive or negative.

We believe we are the first paper to consider the potential and limitations of the information provided by CRA actions. Specifically, we find that the Watch List activity generated by CRAs is associated with GDP. However, when subsamples of the highly regulated insurance industry are separately analyzed, the explanatory power of the variable loses its economic significance. We believe this is either because there is less private information left for CRAs to discover in the insurance industry due to heightened regulatory requirements, or the insurance industry is less susceptible to economic shocks.

Regulation Fair Disclosure (FD) was implemented in October 2002. It forbade public companies from making selective, nonpublic disclosures to favored investment professionals. Importantly, CRAs were excluded from Regulation FD, meaning CRAs were allowed to have more access to private firm information. Jorion et al. (2005) found that the informational effect of CRA activity is greatly increased in the post-Regulation FD era. Likewise, Boot et al. (2006) specifically found evidence to show that CreditWatch Activity helps create a more stable equilibrium between information providers and information seekers. Because the information CRAs collect is not fully available to the public, it has value on its own. Further, the "focal point" communication partially reveals a firm's outlook on its own operational vitality. Therefore, we hypothesize that Watch

List activity reveals information about the length and depth of economic contraction. If firms expected a sustained period of economic tumult and suppressed earnings, Watch List activity could reflect that sentiment.

With respect to highly regulated insurance markets, we hypothesize that there is less private information about insurers to be discovered by CRAs, due to heightened regulatory requirements. Cole et al. (2017) provide some evidence for this hypothesis when studying solicited and unsolicited insurer credit ratings. Unsolicited ratings tend to be based solely on public information and are typically lower than solicited ratings, which depend on proprietary tactics and private information. In the banking sector, Poon (2003) discovered a similar result; i.e., unsolicited rankings—based on public information—tend to result in lower credit ratings. Heightened regulatory requirements lead to more information being divulged publicly, making less private information available to CRAs.

Alternatively, or perhaps concurrently, insurers may be more resilient to economic shocks. The nature of the insurance business is inherently one that emphasizes risk management. Regulation focuses heavily on risk; capital requirements are linked to an explicit recognition of several dimensions of risk. Consequently, this focus may lead insurers to make decisions that emphasize risk management to a greater extent than other industries, which may lead to greater resilience, and it would also lead to less explanatory power contained in Watch List activity. For example, insurers have invested a great deal of time and treasure into trying to assess their exposure to climate risk. Valverde and Convertino (2019) use econometric analysis to assess the macro resilience of insurers to increased catastrophe risk, and they found that insurers are well-positioned to cope.

We can also examine previous analyses of insurer responses to economic shocks. Baluch et al. (2011) examine insurers' performance in the wake of the 2008–2009 financial crisis, and they found that while a heavy correlation between banks' and insurers' returns exists, banks struggled with solvency, while insurers generally did not. They further mention that traditionally, insurers were thought to be largely immune to systemic risk. Cycles are well-known, but the unavailability of insurance is rare. They note that inelastic demand, mandatory coverages, and a lack of available substitutes contribute to insurers' economic security. Cummins and Weiss (2014) also found that the core activities of insurers do not contribute to systemic risk. Eling and Pankoke (2016) found that traditional insurance activity in the life, nonlife, and reinsurance sectors neither contributes to systemic risk nor increases insurers' vulnerability to impairments of the financial system.

In addition, insurers enjoy specific advantages that other industries simply do not. For example, insurers' financial results are somewhat protected from certain large risks due to government guarantees (e.g., terrorism). In the immediate wake of 9/11, the stocks of insurers responded negatively, with better-capitalized insurers rebounding more quickly (Cummins & Lewis, 2002). The federal Terrorism Risk Insurance Act (TRIA) program was initiated to make insurance available by insulating insurers from catastrophic loss (Michel-Kerjan & Kunreuther, 2018). Insurers can also exclude other catastrophic losses that are foreseeable in their contract creation, such as earthquake and flood, adding resiliency. Richter and Wilson (2020) mention that exclusions and fortuitous contract design likely shielded property/casualty (P/C) insurers from large COVID-19 losses. Through an emphasis on risk management in confronting threats to income, and through the abilities of contract design and exclusion that other firms lack, insurers may by their nature be more resilient to economic shock. In that case, the CreditWatch variable we construct will likely not retain its economic significance in our model analyzing subsamples of insurance companies.

3. Data and Methodology

We collect U.S. real GDP growth rates from the U.S. Bureau of Economic Analysis (BEA). The values are quarterly and represent annual change. All values are chained to 2012 dollars. Our CreditWatch List data is collected from Compustat. Our analysis covers 1995–2020. While CreditWatch actions can occur daily, CreditWatch data is pooled quarterly to match our GDP data. We begin our analysis in 1995 due to limited CreditWatch data in previous years. Specifically, 1995 is the first year in which there are more than 200 CreditWatch actions in a particular quarter. For all quarters from 1995 to 2020, there are over 200 observations. In our sample, the minimum number of CreditWatch actions occurs in the first quarter of 1995 with 227 observations. The maximum number of observations occurs in the fourth quarter of 2011 with 1,609 CRA alerts.

We focus our attention on Watch Positive and Watch Negative CRA actions. Our final sample includes 68,167 CreditWatch actions, with 53,001 CreditWatch Negative warnings and 15,166 CreditWatch Positive alerts. After pooling all observations into the appropriate quarter, we create a *WatchRatio* variable. This ratio contains the number of Watch Negative actions for each quarter in the numerator and the number of Watch Positive actions for each quarter in the denominator. We expect this value to be negatively correlated with GDP.

Based on the credit rating literature, we hypothesize that CRA Watch alerts are tied to economic activity. To test our position, we first regress several economic indicators that are known to correlate with GDP (Stock & Watson, 1989). Specifically, we regress *ISMManufacturing, ChangeInNonfarmPayrolls,* and *HousingStarts* on our GDP variable. The *ISMManufacturing* variable is the Purchasing Managers' Index (PMI), and is based on a survey of manufacturing supply executives. The survey results are quantified and made available by the Institute for Supply Management (ISM). Our *ChangeInNonfarmPayrolls* variable is calculated by the U.S. Bureau of Labor Statistics (BLS), and it measures the number of workers in the economy, excluding proprietors, private household employees, unpaid volunteers, farm employees, and the unincorporated self-employed. Finally, the U.S. Census Bureau and U.S. Department of Housing and Urban Development (HUD) estimate housing starts, including units being rebuilt on an existing foundation. These housing starts are represented by the *HousingStarts* variable.

After confirming the validity of these independent variables by examining Adjusted R-Squared, p-values, and F-values, we then add our CreditWatch variable as an additional independent variable. We then rerun the regression with the new independent variable, once again focusing on the validity of the regressors and the power of the model.

Next, we quantify the relationship between GDP and our *WatchRatio* variable. We do so by examining the change in our *WatchRatio* relative to the change in GDP in previous economic downturns. We compare these results to the result from the duration of the COVID-19 recession to see if they are similar.

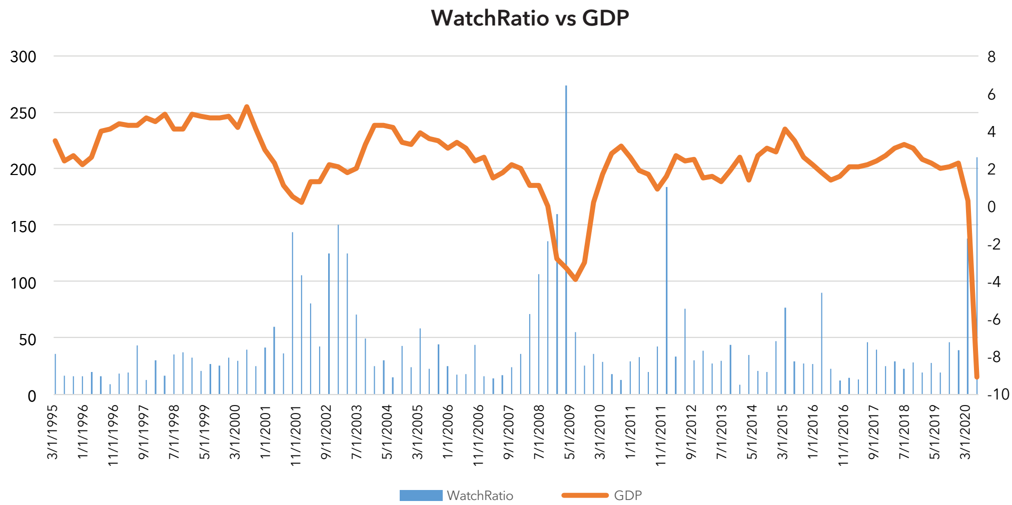
We then create subsamples of life/health insurance companies and P/C insurance companies and analyze them separately. Of our 68,167 firm/quarter CreditWatch observations, 2,843 involve life/health companies—identified by Standard Industrial Classification (SIC) codes 6310 and 6311—and 5,363 involve P/C companies—identified by SIC codes 6330 and 6331.

Results

We find that: 1) our newly created CreditWatch variable has statistical and economic significance; 2) when applied to the second quarter of 2020—i.e., the quarter involving COVID-19—it might have been able to provide evidence that the stock market reaction associated with the radical drop in GDP was potentially an overreaction; and 3) when we analyze two subsamples of life/health insurers and P/C insurers, the economic significance of the CreditWatch variable disappears.

Figure 1 plots *WatchRatio* against GDP. A cursory glance at the figure reveals spikes in *WatchRatio* when GDP is declining. To quantify our position, we regress our *WatchRatio* variable onto GDP, using years 1995–2019. Our intention is then to use these results to examine expected activity in 2020. The value of these results is limited, as CreditWatch activity where negative watches dramatically exceed positive watches is only available for the previous two recessions, in addition to the one brought on by COVID-19. Results from regressing *WatchRatio* onto GDP are seen contemporaneously in Table 1 and lagging in Table 2, and they show that our independent variable is significant at the 1% level in both cases, which is discussed later. We use this regression to extract the expected economic contraction when our *WatchRatio* value takes a value of 21, which is the calculated value in the second quarter of 2020. Using the regression coefficient, we calculate the expected GDP at approximately -4.25%. However, GDP contraction was much greater at -9.1%. Equity markets followed economic contraction and dropped markedly in the second quarter. Our indicator suggests that the equity market plunge was possibly unwarranted, as CRAs, with insider information, did not rate commensurately. Instead, our indicator value during that time would have been expected to be associated with a slight pull back in domestic production.

Figure 1



The orange line indicates quarterly U.S. real GDP data, representing annual change, and it is chained to 2012 dollars. The WatchRatio is calculated as the number of CreditWatch Negative warnings divided by the number of CreditWatch Positive alerts. The left y-axis is associated with WatchRatio values for the entire sample, while the right y-axis is associated with GDP. The data covers 1995–2020.

Table 1

Variable	(1)	(2)	(3)	(4)
ISMManufacturing	0.1852***	0.0886***	0.1719***	0.1753***
	(0.033)	(0.033)	(0.033)	(0.033)
ChangeInNonfarmPayrolls	0.0014***	0.0012***	0.0015***	0.0015***
	(0.000)	(0.000)	(0.000)	(0.000)
HousingStarts	0.0022***	0.0019***	0.0022***	0.0023***
	(0.000)	(0.000)	(0.000)	(0.000)
WatchRatio		-0.1948***	-0.0138**	-0.0055**
		(0.032)	(0.007)	(0.003)
Adjusted R^2	0.4517	0.5932	0.4698	0.4691
F Value	28.73***	37.82***	23.38***	23.32***
N	102	102	102	102

The sample includes 1995–2020 and regresses economic variables of interest on the dependent variable: U.S. real GDP_t. Values are quarterly, and the independent variables are *ISMManufacturing*$_t$, *ChangeInNonfarmPayrolls*$_t$, *HousingStarts*$_t$, and *WatchRatio*$_t$, which is defined as the number of CreditWatch Negative actions divided by the number of CreditWatch Positive actions for a particular quarter. Column 2 is the full sample. Column 3 is for Life Insurance companies (SIC 6310/6311), and Column 4 is for P/C companies (SIC 6330/6331). Standard errors are given in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

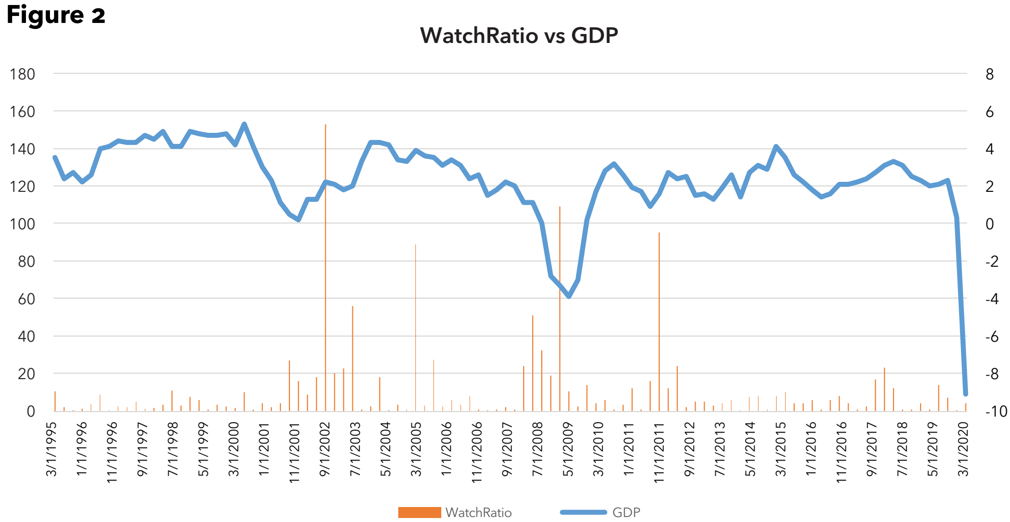
Table 2

Variable	(1)	(2)	(3)	(4)
ISMManufacturing	0.1852***	0.1098***	0.1742***	0.1719***
	(0.033)	(0.031)	(0.032)	(0.033)
ChangeInNonfarmPayrolls	0.0014***	0.0013***	0.0015***	0.0015***
	(0.000)	(0.000)	(0.000)	(0.000)
HousingStarts	0.0022***	0.0020***	0.0022***	0.0022***
	(0.000)	(0.000)	(0.000)	(0.000)
WatchRatio		-0.1968***	-0.0169**	-0.0049*
		(0.033)	(0.006)	(0.003)
Adjusted R^2	0.4517	0.5914	0.4824	0.4646
F Value	28.73***	37.55***	24.54***	22.91***
N	102	102	102	102

The sample includes 1995–2020 and regresses economic variables of interest on the dependent variable: U.S. real GDP_t. Values are quarterly, and the independent variables are $ISMManufacturing_t$, $ChangeInNonfarmPayrolls_t$, $HousingStarts_t$, and $WatchRatio_{t-1}$, which is defined as the number of CreditWatch Negative actions divided by the number of CreditWatch Positive actions for the t-1 quarter. Column 2 is the full sample. Column 3 is for Life Insurance companies (SIC 6310/6311), and Column 4 is for P/C companies (SIC 6330/6331). Standard errors are given in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

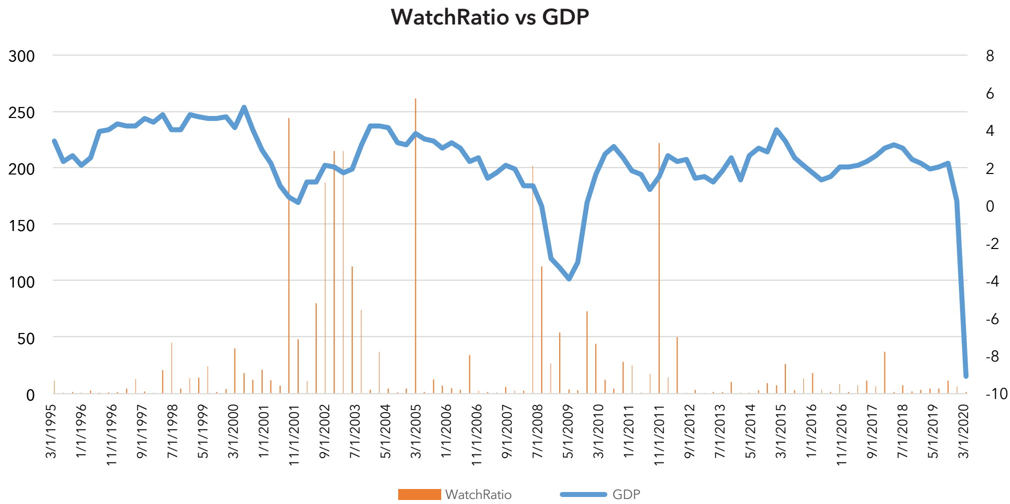
By comparison, we apply our regression formula to the two previous economic recessions as a baseline. These values and patterns for the entire sample can also be visually seen in Figure 1. The associated values for subsamples consisting of only life/health and P/C insurance companies, respectively, are plotted in Figures 2 and 3. Casual observation provides a hint of our ultimate results; i.e., the relationship between the *WatchRatio* variable and GDP for the subsamples is less obvious.

Figure 2



The blue line indicates quarterly U.S. real GDP data, representing annual change, and it is chained to 2012 dollars. The WatchRatio is calculated as the number of CreditWatch Negative warnings divided by the number of CreditWatch Positive alerts for Life Insurance companies (SIC 6310/6311). The left y-axis is associated with WatchRatio values for the entire sample, while the right y-axis is associated with GDP. The data covers 1995–2020.

Figure 3



The blue line indicates quarterly U.S. real GDP data, representing annual change, and it is chained to 2012 dollars. The WatchRatio is calculated as the number of CreditWatch Negative warnings divided by the number of CreditWatch Positive alerts for P/C Companies (SIC 6330/6331). The left y-axis is associated with WatchRatio values for the entire sample, while the right y-axis is associated with GDP. The data covers 1995–2020.

For the entire sample, at the start of the last recession in the fourth quarter of 2008, our *WatchRatio* indicator read 15.98. Expected GDP with this reading would have been approximately -3.25%. Actual GDP was -2.8%—and another negative GDP quarter followed—supporting the value of our *WatchRatio* variable. Further, in the first quarter of 2001, our indicator read 2.6, suggesting an economic contraction of -0.5%, compared with the actual GDP contraction of -1%. While limited in sample, we find reasonable explanatory power with our *WatchRatio* variable from these three specific data points. Confidence in this variable could have provided foresight to market participants. Table 1 will provide more evidence of the value of this variable, which is discussed below.

With our indicator, we can hypothesize that CRAs, with private insider information, did not believe firms would suffer long-term from the COVID-19 recession. As a result, CRAs' rating activities were not in line with the actual GDP. Instead, CreditWatch actions revealed CRA expectations of a slowing economy, but not a relatively extreme GDP contraction of -9%. In hindsight, we surmise that an opportunity to spot the quick recovery may have been available to those who closely monitor Watch List activity.

Table 1 presents our regression results. *ISMManufacturing, ChangeInNonfarmPayrolls,* and *HousingStarts* are all significant independent variables at the 1% level, confirming prior research. This is in line with expectations, as these variables are widely accepted economic indicators. The model returns an adjusted R^2 of 0.4516 and a significant F value, confirming the validity of our model. We then rerun the regression, with an added independent variable that captures CreditWatch activity, *WatchRatio*, in Column 2. As predicted, the *WatchRatio* variable is negatively correlated to GDP and significant at the 1% level. Additionally, all other independent variables remain significant at the 1% level. We also consider changes in adjusted R^2 and find improvement with the new model, validating our newly created measure as an economic indicator that adds explanatory power to the model.

Table 1 also presents the results of separately examined insurance companies, compared to the full sample. Column 2 reports results for the entire sample, while Column 3 reports results for life/health insurers, and Column 4 reports results for P/C insurers. We can see that for both life/health and P/C insurers, the power of the *WatchRatio* is significantly reduced; although, the coefficients remain significant at the 0.05 level, rendering them statistically but not economically significant. One explanation is our first hypothesis; i.e., there is simply less private information to discover since insurers are highly-regulated and already required to submit more detailed information to state insurance regulators. Another explanation is our second hypothesis; i.e., because of a focus on risk management activities and the ability to structure contracts and exclusions, the insurance industry is more resilient to economic downturn; thus, CreditWatch activity will have less explanatory power when applied to insurers.

We further test the initial results from Table 1 in Table 2 by using observations from GDP at time *t* and *WatchRatio* at time *t-1*. There are no substantial statistical differences, thus adding robustness to our original results found in Table 1.

4. Conclusion

We examine the association of CRA activity proxied by Watch List activity with GDP. After establishing that the Watch List variable we created has explanatory power, we consider its relationship to GDP during the three recessions contained in our sample period. As shown in Figure 1, during the first two recessions, we notice that our variable is consistently associated with the GDP decline. In Figures 2 and 3, for the subsamples including only life/health insurers and P/C insurers, respectively, we visually note that the relationship between our CreditWatch variable and GDP does not seem to be as strong, a result that is bolstered by our empirical analysis in Columns 3 and 4 of Table 1. We note that there was a relatively swift economic and equity recovery following the economic contraction related to COVID-19, and we show that Watch List activity was associated with a projected economic pause less grand than the actual GDP number revealed. Upon examination, our newly created indicator, *WatchRatio*, was not associated as strongly with the economic downturn as our regression model would have expected. Consequently, equity investors may have had an opportunity to foresee the rapid market recovery based on private information communicated through CRA alerts.

We chose to apply our new variable to subsamples containing firms in the highly regulated insurance industry for two reasons: 1) we believe the insurance industry has less private financial information available to discover due to heightened required regulatory disclosures; and 2) the insurance industry may also be more resilient to economic shocks by its very nature. We find a dramatic difference when analyzing the insurance sector of the economy. The explanatory power of our newly created indicator, *WatchRatio*, is significantly reduced when analyzing both life/health insurers and P/C companies. This result can be explained by less private information being available to discover because of heightened regulatory requirements, and it could alternatively or concurrently be explained by the relative economic resilience of the insurance industry.

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