University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2019-67
August 2019

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Gold, Platinum and the Predictability of Bond Risk Premia

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This version: August 2019

We show that the ratio of gold to platinum prices (GP) contains significant predictive information for excess U.S. government bond returns, even after controlling for a large number of financial and macro factors. Including GP in the model improves the predictive accuracy, over and above the standard macroeconomic and financial predictors, at all forecasting horizons for the shortest maturity bonds and at longer forecasting horizons for bonds with longer maturities beyond 2 years. The findings highlight the predictive information captured by commodity prices on bond market excess returns with significant investment and policy making implications.

JEL classification: C22; C53; G12; G17; Q02

Keywords: Bond Premia; Predictability; Gold-Platinum Price Ratio; Out-of-Sample Forecasts

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1. Introduction

The role of U.S. Treasury securities as a global safe haven is well-established, primarily due to the significant lack of default risk in these assets and the status of the U.S. dollar as a reserve currency (e.g. Kopyl and Lee, 2016; Habib and Stracca, 2017; Hager, 2017; Demirer and Gupta, 2018; Gupta et al., 2018). At the same time, the yields on short and long-term Treasuries are shown to capture valuable information regarding the current and future states of the economy and inflation (e.g. Hamilton and Kim, 2002; Dewachter et al., 2014; Gogas et al., 2015a,b; Plakandaras et al., 2017a,b, forthcoming; Pierdzioch and Gupta, 2019). Given the significance of U.S. Treasury securities both in terms of economic forecasting models as well as portfolio allocation decisions, a large and growing literature exists on forecasting excess returns on U.S. government bonds (e.g. Cochrane and Piazzesi, 2005; Ludvigson and Ng; 2009, 2011; Laborda and Olmo, 2014; Zhu, 2015; Ghysels et al., 2018; Gargano et al., 2019; Çepni et al., 2019, forthcoming).[1] In general, the empirical evidence highlights the role of macro and financial factors (often extracted from large data sets), as well as behavioral predictors (investor sentiment and risk-aversion) in predicting bond premia, over and above the so-called CP factor of Cochrane and Piazzesi (2005), constructed as a linear combination of forward rates. Clearly, the predictability of risk premia on U.S. Treasuries is of interest for not only investment allocation decisions, but also for market timing and policy making purposes due to the information they capture regarding future economic conditions.

Against this backdrop, the objective of this paper is to analyze for the first time, the role of commodity prices, in particular the ratio of gold to platinum prices (GP), in forecasting U.S. government bond risk premia, after controlling for a number of well-established predictors including the CP factor and a large number of macro and financial factors. The use of GP as a potential predictor is motivated by the recent evidence in Huang and Kilic (2019) that this ratio serves as a proxy for aggregate market risk, displaying countercyclical behavior, and that it serves as a strong predictor of equity returns, both in the U.S. and internationally, outperforming nearly all existing return predictors. Considering that gold can be viewed both as a consumption good (mostly jewelry) and an investment tool that preserves value during times of distress, while platinum is a precious metal with similar uses as gold in consumption, Huang and Kilic (2019) argue that GP should be largely insulated from shocks to consumption and jewelry demand, and

[1] Notable earlier studies include Keim and Stambaugh (1986), Fama and Bliss (1987), Fama and French (1989), and Campbell and Shiller (1991).

instead, thus provide information on variation in aggregate market risk, serving as a proxy for an important economic state variable.[2]

While we conduct both in- and out-of-sample predictability analysis, we primarily focus on the out-of-sample forecasting of excess bond returns, given the widely held view that the importance of variables and models should be judged based on out-of-sample validations (Campbell, 2008). We show that GP indeed serves as a strong predictor for excess bond returns over and above the traditional predictors based on forward rates and macro variables. Including GP in the model improves the predictive accuracy at all forecasting horizons for the shortest maturity bonds and at longer forecasting horizons for bonds with longer maturities beyond 2 years. The findings highlight the predictive role of commodity market based variables in bond market forecasting with significant implications for asset allocation and policy making decisions. The remainder of the paper is organized as follows: Section 2 provides the description of the data and methodology, Section 3 presents the empirical results, while Section 4 concludes the paper.

2. Data and Methodology

Price data for one through five-year zero coupon bonds at monthly frequency are obtained from the Fama and Bliss (1987) dataset, which is available at the Center for Research in Security Prices (CRSP).[3] Gold and platinum prices are the monthly average of daily fixing prices from the London Bullion Market Association (LBMA) and London Platinum and Palladium Market (LPPM) obtained from the Datstream database of Thomson Reuters.[4] Based on the availability of data, our sample period runs from 1960:03 to 2016:12.

[2]Huang and Kilic (2019) develop a theoretical model where GP is insulated from shocks to consumption, since they affect gold and platinum prices equally, in which increases in disaster probabilities raise risk premiums, leading to higher discount rates and lower stock prices. While gold and platinum prices fall due to higher discount rates, gold prices fall by less than platinum prices due to the higher countercyclical component of its service flow. As a result, GP is shown to be high when stock prices are low and the equity risk premium is high, thus providing GP the power to predict future stock returns.

[3]In line with Cochrane and Piazzesi (2005), we use the following notation for the (log) yield of an n-year bond $y_t^{(n)} \equiv -\frac{1}{n} p_t^{(n)}$, where $p_t^{(n)} = lnP_t^{(n)}$ is the log bond price of the n-year zero coupon bond at time t. A forward rate at time t for period ($t+n-1$, $t+n$) is defined as: $f_t^{(n)} \equiv p_t^{(n-1)} - p_t^{(n)}$. The log holding period return from buying an n-year bond at time t and selling it as an $n-1$ year bond at time $t+1$ is: $r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)}$. The excess return on an n-year discount bond over a short-term bond is then the difference between the holding period returns of the n-year bond and the 1-period interest rate, $rx_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)}$.

[4]As in Huang and Kilic (2019), we use prices from the a.m. fixing, which is conducted at 9:45 a.m. GMT (for platinum) and 10:30 a.m. GMT (for gold).

In order to analyze the predictability of excess bond returns, we run predictive regressions of the type commonly used in the empirical finance literature, formulated as

$$rx_{t+1}^{(n)} = \alpha_0 + \beta' Z_t + \varepsilon_{t+1}, \tag{1}$$

where $rx_{t+1}^{(n)}$ is the continuously compounded excess return on an n-year zero coupon bond in period $t+1$. Besides the benchmark random-walk (RW) model, we estimate two additional models: (i) with Z_t including the single forward factor (CP) of Cochrane and Piazzesi (2005)[5], and the macro factors (LN) constructed by Ludvigson and Ng (2009, 2011) via dynamic factor analysis.[6]; and (ii) with Z_t including the ratio of gold to platinum prices (GP) as well as the CP and LN factors. Next, comparing the second model with the first, we explore whether GP captures predictive information over and above that is contained in CP and LN.

Although Ludvigson and Ng (2009, 2011) find that nine common factors explain more than 50% of the variation in macro series, we follow Cochrane and Piazzesi (2005) and form a single predictor, F_s, by estimating a regression of average excess returns on the set of estimated nine factors. Hence, we construct a linear combination of factors that explains a large fraction of the variation in future excess returns by running the following regression:

$$\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \gamma_0 + \gamma_1 \widehat{F_{1t}} + \gamma_2 \widehat{F_{1t}^3} + \gamma_3 \widehat{F_{2t}} + \gamma_4 \widehat{F_{3t}} + \gamma_5 \widehat{F_{4t}} + \gamma_6 \widehat{F_{5t}} + \gamma_7 \widehat{F_{6t}} + \gamma_8 \widehat{F_{7t}} + \gamma_9 \widehat{F_{8t}} = F_s \tag{2}$$

In order to examine how much of the variation in excess bond returns can be explained by different factors, we first run in-sample regressions as shown in Eq.(1). We then conduct a recursive out-of-sample forecasting exercise from 1981:01 to 2016:12 (given an in-sample 1960:03 to 1980:12) to analyze the predictive accuracy of alternative model specifications. We choose the in- and out-of-sample periods, based on the evidence of a shift in the term-structure in 1980 (believed to be a result of Paul Volcker's strong disinflationary policies to curb double digit inflation rates in the US, which, to some extent, was due to the second major oil-price shock in 1979), as suggested by Smith and Taylor (2009) and more recently by Balcilar et al., (forthcoming). Note that the specification of the out-of-sample period allows us to cover

[5] To compute the CP predictor, we first regress average excess returns across maturities at each time t on the one-year yield and the forward rates $f_t \equiv [y_t^{(1)} f_t^{(2)} f_t^{(3)} f_t^{(4)} f_t^{(t)}]^T$: $\overline{rx}_{t+1} = \gamma_0 + \gamma^T f_t + \overline{\varepsilon}_{t+1}$, where the average excess log returns across the maturity spectrum is defined as: $\overline{rx}_{t+1} \equiv \frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)}$. The CP predictor is then obtained from: $CP_{t+1} = \gamma_0 + \gamma^T f_t$.

[6] Data obtained from Sydney C. Ludvigson's website at: https://www.sydneyludvigson.com/data-and-appendixes/.

most of the important crisis periods experienced in global financial markets. For each month, we produce a sequence of eight h-month-ahead forecasts for $h = 1, 3, 6, 12, 24, 36, 48, 60$, and compute mean square forecast errors (MSFEs) for each model. Finally, we use the $MSE - F$ test of McCracken (2007) in order to evaluate whether the forecast performances are statistically different across the various nested models.

3. Empirical Results

Although the main focus of our study is out-of-sample forecasting, we first briefly discuss the in-sample results for the full sample (1960:03 to 2016:12), reported in Table 1. We observe that GP has strong in-sample predictive ability (at the 1% level of significance) across all maturities examined, in line with the findings reported by Huang and Kilic (2019) for excess stock returns. Furthermore, we find that the predictive power of GP increases with the forecast horizon, consistently across the maturities of 2-, 3-, 4-, and 5-year, implied by the higher values of the regression coefficient on GP. To that end, in-sample analysis provides strong support for the predictive value of GP for excess bond returns.

– Insert Table 1 about here. –

Given that in-sample predictability does not guarantee out-of-sample gains, we present in Table 2, the forecasting results based on alternative model specifications. For each of the four maturities examined (2-, 3-, 4-, and 5-years), the first row in the table provides the MSFE of the benchmark random walk (RW) model. Models that yield the lowest relative MSFE values (relative to the RW) at each horizon h are denoted in bold in the second and third rows. In order to examine whether GP provides any additional predictive value over and above that is captured by the well-documented CP and F_s predictors, in row four of each panel, we present the relative MSFE of the complete model that includes CP, F_s and GP as predictors, compared to the model with CP and F_s only. The last row is the most important in our context as it provides insight to whether adding the commodity market based predictor can improve the forecasting performance of the model beyond the two well-established predictors of CP and F_s for bond premium.

We observe in Table 2 that the models which include CP, F_s and GP (reported in rows 2 and 3 in each panel) consistently outperform the benchmark RW model, underlining the predictive information captured by these well-established predictors for bond excess returns as well as the GP predictor. We also note that the forecasting gains (relative to the RW model) tend to be higher at shorter forecasting horizons, suggesting that predictive information captured in implied forward rates and macroeconomic variables concentrate primarily on short-term market dynamics. Examining the fourth row in each panel, we observe that GP indeed serves as a strong predictor for excess bond returns over and above the traditional predictors based on forward rates and macro variables. The predictive power of GP is particularly strong and consistent in the case of short-term bond risk premia ($rx_{t+1}^{(2)}$) with the complete model that includes CP, F_s and GP providing more accurate out-of-sample forecasts compared to the RW+CP+F_s model at all forecast horizons. In the case of maturities beyond two years, however, we see that the role of GP in producing more accurate forecasts relative to CP and F_s factors is primarily concentrated at longer horizons. We observe that GP provides additional forecasting power at h=12 and beyond for 5-year maturity bond excess returns and for h=24 and beyond for 3- and 4-year maturity excess returns. To that end, consistent with the in-sample evidence, out-of-sample results suggest that forecasting gains derived from GP over and above CP and F_s predictors tend to increase as the forecasting horizon increases. While the standard predictors CP and F_s used in the literature tend to produce relatively more accurate forecasts at shorter forecasting horizons, especially for bond premia associated with longer maturities beyond two years, we find that the predictive power of GP allows for more accurate forecasts at longer forecast horizons.

An important question is whether the models with predictor combinations of (CP and F_s) and (CP, F_s and GP) outperform the benchmark RW specification in a statistically significant manner, and whether the same holds true for the full model with CP, F_s and GP relative to the nested model with CP and F_s. As stated earlier, we compare alternative model specifications by examining whether the $MSE - F$ test is statistically significant or not. This procedure allows us to formally test whether the null of equal forecast accuracy can be rejected, given the alternative hypothesis that the unrestricted model (i.e., RW+CP+F_s or RW+CP+F_s+GP) outperforms the restricted model (i.e., RW or RW+CP+F_s). As can be seen from Table 2, the two models (RW+CP+F_s and RW+CP+F_s+GP) significantly outperform the RW model at the 1% level of significance based on the $MSE - F$ test at all horizons and across the bond maturities, with the only exception being h=48 for the bond premium with the longest maturity under the RW+CP+F_s model. In terms of our primary interest, the RW+CP+F_s+GP model statistically outperforms the RW+CP+F_s model in all cases at 1% level except for h=3 for the bond premium with the shortest maturity where the relative MSFE value was less than one. In short, barring a few exceptions, we observe that including the GP predictor in the model yields statistically significant forecasting gains, particularly for longer maturity bonds beyond two years and at longer forecast horizons.

The predictive value observed for the ratio of gold to platinum prices, particularly for longer maturity

Treasuries and at longer forecast horizons, suggests that shocks to gold prices do not necessarily reflect short-term, flight-to-liquidity concerns in the market place and instead, capture market uncertainties that are longer-term in nature. This argument is supported by the observation in Huang and Kilic (2019) that shocks to GP do not correlate with shocks to transient measures of liquidity risk. While the significant results observed in favor of GP in the case of the shorter maturity bond premia could be a manifestation of the short-term market information captured by shocks to gold prices, the consistent evidence reported for longer maturity bond premia suggests that variations in GP capture changes in long-run disaster risk probabilities as reported by Wachter (2013) for the equity market. Nevertheless, the findings provide novel insight to the predictive information captured by commodity prices over excess returns on Treasury securities over and above that is contained in traditional financial market based predictors.

– Insert Table 2 about here. –

4. Conclusion

This paper shows that the ratio of gold and platinum prices (GP) possesses significant predictive value (both in- and out-of-sample) for excess returns on U.S. government bonds even after controlling for a large number of financial and macro factors. The predictive value of GP is particularly notable over both shorter and longer forecast horizons for excess bond returns with a maturity of 2-year, and for longer forecast horizons for excess returns on bonds with maturities of 3-, 4-, and 5-year. The findings suggest that commodity price movements indeed capture valuable predictive information over the evolution of future interest rates, which can help policymakers to fine-tune their monetary policy models. Furthermore, investors can improve asset allocation strategies by exploiting the role of GP in their interest-rate prediction models. Finally, researchers may utilize our findings to explain deviations from asset-pricing models of random walk, by embedding gold to platinum price ratio in their pricing models. While we concentrate on U.S. Treasury securities, as part of future research, it would be interesting to extend our analysis to the bond market of other developed and emerging countries.

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Table 1: In-sample regressions of monthly excess bond returns based on the gold to platinum price ratio as a predictor

				$rx_{t+1}^{(2)}$				
	h=1	h=3	h=6	h=12	h=24	h=36	h=48	h=60
GP	0.0074***	0.0226***	0.0454***	0.0896***	0.1667***	0.2312***	0.2745***	0.3126***
				$rx_{t+1}^{(3)}$				
	h=1	h=3	h=6	h=12	h=24	h=36	h=48	h=60
GP	0.0098***	0.0303***	0.0607***	0.1211***	0.2251***	0.3020***	0.3501***	0.3929***
				$rx_{t+1}^{(4)}$				
	h=1	h=3	h=6	h=12	h=24	h=36	h=48	h=60
GP	0.0155***	0.0476***	0.0953***	0.1906***	0.3557***	0.4768***	0.5678***	0.6531***
	h=1	h=3	h=6	h=12	h=24	h=36	h=48	h=60
				$rx_{t+1}^{(5)}$				
	h=1	h=3	h=6	h=12	h=24	h=36	h=48	h=60
GP	0.0190***	0.0586***	0.1174***	0.2358***	0.4439***	0.5935***	0.7222***	0.8470***

Note: The table reports the estimates from OLS regressions of excess bond returns on the gold to platinum price ratio (GP) for various forecasting horizons in columns. A constant is always included in the regressions. Standard errors are reported in parentheses. Entries superscripted with *** denote statistical significance at the 1% level.

Table 2: Out-of-sample forecasting of excess bond returns based on alternative model specifications

$rx_{t+1}^{(2)}$	h=1	h=3	h=6	h=12	h=24	h=36	h=48	h=60
RW	0.0197	0.0578	0.1120	0.2120	0.3739	0.5060	0.6222	0.7230
(RW+CP+F_s)/RW	0.4016***	0.3607***	0.3753***	0.3459***	0.3877***	0.6865***	0.9680***	0.9703***
(RW+CP+F_s+GP)/RW	**0.3951*****	**0.3586*****	**0.3750*****	**0.3406*****	**0.3598*****	**0.5958*****	**0.8034*****	**0.7804*****
(RW+CP+F_s+GP)/(RW+CP+F_s)	0.9837***	0.9941**	0.9993	0.9845***	0.9281***	0.8679***	0.8299***	0.8044***
$rx_{t+1}^{(3)}$	h=1	h=3	h=6	h=12	h=24	h=36	h=48	h=60
RW	0.0364	0.1066	0.2062	0.3869	0.6689	0.8942	1.0965	1.2687
(RW+CP+F_s)/RW	**0.4388*****	**0.4054*****	**0.4149*****	**0.3840*****	0.4243***	0.7086***	0.9357***	0.9213***
(RW+CP+F_s+GP)/RW	0.4524***	0.4085***	0.4174***	0.3898***	**0.4237*****	**0.6773*****	**0.8493*****	**0.8150*****
(RW+CP+F_s+GP)/(RW+CP+F_s)	1.0311	1.0077	1.0061	1.0151	0.9986	0.9559***	0.9076***	0.8845***
$rx_{t+1}^{(4)}$	h=1	h=3	h=6	h=12	h=24	h=36	h=48	h=60
RW	0.0519	0.1520	0.2942	0.5507	0.9478	1.2683	1.5686	1.8379
(RW+CP+F_s)/RW	**0.4699*****	**0.4343*****	**0.4445*****	**0.4297*****	0.4998***	0.7878***	0.9842***	0.9591***
(RW+CP+F_s+GP)/RW	0.4829***	0.4370***	0.4457***	0.4307***	**0.4834*****	**0.7333*****	**0.8777*****	**0.8386*****
(RW+CP+F_s+GP)/(RW+CP+F_s)	1.0277	1.0061	1.0028	1.0023	0.9673***	0.9308***	0.8918***	0.8744***
$rx_{t+1}^{(5)}$	h=1	h=3	h=6	h=12	h=24	h=36	h=48	h=60
RW	0.0646	0.1884	0.3638	0.6777	1.1570	1.5483	1.9258	2.2693
(RW+CP+F_s)/RW	**0.5024*****	**0.4702*****	**0.4792*****	0.4635***	0.5312***	0.8197***	1.0078	0.9732***
(RW+CP+F_s+GP)/RW	0.5166***	0.4737***	0.4804***	**0.4629*****	**0.5098*****	**0.7563*****	**0.8912*****	**0.8447*****
(RW+CP+F_s+GP)/(RW+CP+F_s)	1.0283	1.0073	1.0024	0.9987	0.9597***	0.9226***	0.8844***	0.8680***

Note: Entries in the first row of the table are point MSFEs based on the benchmark random walk (RW) model, while the rest are relative MSFEs, with the last row corresponding to relative MSFE of the complete model with CP, F_s and GP with respect to the RW+CP+F_s model. Hence, a value of less than unity indicates that a particular model is more accurate than that of the RW model, for a given forecast horizon. Models that yield the lowest MSFE for each forecast horizon are denoted in bold. Entries superscripted with *** and ** are significantly superior than the benchmark RW model and the RW+CP+F_s model, based on McCracken's (2007) $MSE-F$ test, at the 1% and 5% level, respectively.