Gold Risk, Crash Fear and Expected Stock Returns

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Abstract

Using a model-free approach, we derive an economic crash fear index based on the short-maturity options on gold futures. The index predicts future stock returns, explain the variation in the cross-section of stock returns and it is significantly correlated with the option-based tail risk measures. The fear index also is related to the other economic disaster indices in the literature. Finally, the index shows considerable power in predicting prominent macroeconomic and fear indices. We augment our measure using price of precious metals and show the same results hold in longer samples using the new measure.

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I. Introduction

Gold has always been one of the commodities which brings the highest level of attention to itself in economics and finance. In contrast to the general understanding about the role of gold in the economy, which concentrates on its role in jewelry industry, gold is a multi-facet and complex entity which plays a plethora of economic roles, beside its traditional role of being a valuable part of jewelry industry. In general, gold has a three-dimensional role in the macroeconomy of the world. The first role gold plays is the role of the metal in producing different products, specifically in medical and high-tech industries. The second usage of gold is the demand for this metal in jewelry industry. The third one, which is the most important one from our point of view in finance, is the role gold plays in storing the value of people's wealth at the time of adverse macroeconomic conditions. (Baur and McDermott (2010) , Reboredo (2013), Baur and Lucey (2010), etc.)

The role of gold as a "safe haven" for adverse macroeconomic conditions makes the commodity a very special one. As widely known, the value of gold and gold-producing companies tend to be negatively correlated with most of the macroeconomic indices. The reason is that in the time of adverse macroeconomic conditions, gold is one of the first assets which grabs the attention of investors to hedge their wealth against economic crash and distress. This makes it an appealing case to estimate an approximation for the safe haven demand channel in the price of gold, using financial derivatives in the gold market. In other words, this index would be a very good approximation for the level of macroeconomic distress from the perspective of investors.

The biggest impediment for extracting the safe haven demand channel in gold market is that the price of gold, like the price of any other commodity, is the equilibrium of all different forces in gold market, not the effect of one single channel. This reminds us of a very popular challenge in commodity finance which is disentangling supply and demand forces. (Kilian (2009) , Liu et al. (2016), Baumeister and Hamilton (2019), Lin (2008), etc.) Here and in this paper, we use the power provided by options data on gold futures contracts, which are one of the most liquid among the commodity options and cover a relatively long period of time (1986-2020), to estimate the safe haven channel. Here, because of the lack of liquidity in the commodity options market before the industrialization, which started in around 2004, we only consider the 2004-2020 sub-sample. We also do not include the data related to year 2020 because we do not want the impact of the Covid-19 effect on the jump in gold price to be the driver of the results we get out of our analysis.

The use of options contracts in order to isolate the safe haven channel among all the forces in the time series of gold price needs some additional explanation. There are two additional factors provided by options data which add to the benefits of using it. The first one is that for any underlying we have options which are used to hedge the upside risk (call options) and the options that cover downside (put options). We can disentangle the upside and downside risks using options contracts, with the help of this characteristic. The second added value of the options data is that it provides an additional dimension of data, strike prices, which makes it possible to detach the possibility of occurrence of price variations with different sizes.

Options data enables us to use very simple mathematical techniques and results to easily disentangle the continuous price variation, which we call the risk-neutral diffusion, and the non-continuous price variation which is called risk-neutral jump. Ebrahimi and Pirrong (2019) do the same thing in the case of oil market. The paper shows while the variance measure extracted from the oil options data is mainly driven by the demand side factors of the market, the jump component is mostly related to the variables which are directly or indirectly tied to variation in supply of oil.

The link between diffusion (jump) components and demand (supply) can be intuitively described in the case of oil market. Oil is an strategic commodity which its producers have huge economic and geopolitical interests in changing its price intentionally. As a result, jumps in the oil market mainly come from supply disruption and problems in the supply side. Also, the demand of oil works as a steady and continuous flow from all the producers that use the commodity for production. From this point of view, gold is a totally different commodity than oil. We mentioned earlier than the main usages of gold are industry, jewelry and safe haven usage for storing the value of the wealth for different economic players. Intuitively, there should not be any surprising (jump) component in industrial and jewelry use of gold, as these two are main factors of total macroeconomic growth and consumption which grows smoothly, almost all the time. This means that these two channels are expected to be the building blocks of the diffusion component. As described before, gold is a very popular asset to hedge against the macroeconomic downturns. As a result, there will be a rush to buy gold to save the value of wealth at the time of macroeconomic distress and turmoil. This implies that the most related factor among the three components to the risk-neutral jump is the safe haven demand. We try to utilize options data to disengage these different channels in gold prices.

Bollerslev and Todorov (2011) show that for quantifying the risk-neutral jump component, we can use very short time to maturity options. The present value of these option prices can be a reliable measure of risk-neutral jump. As jump is a concept which is conditional on size, we need to determine which level of moneyness will be picked to be used among all the options data we have. We prefer to use all the options and as a result we need to come up with a measure which summarizes all the options data. This can be in contrast to the gist of their argument, as they show in order to be able to successfully separate jumps from diffusion we need to avoid using near-the-money options. In their work, they try to come up with a rule for choosing a threshold that should be picked as a cutoff to make sure we are effectively separating diffusion and jump components. To resolve the problem, we use an approach similar to the Bollerslev and Todorov's to make sure that we are using a broad set of options data and not having the problem of using near-the-money options at the same time. We then use this index in order to predict stock market returns and macroeconomic indices which is in-line with the time-varying rare macroeconomic disaster literature. (Berkman et al. (2011), Wachter (2013), Gabaix (2012), Barro (2006), Rietz (1988) etc.)

We test the ability of the index we calculated in predicting the value-weighted stock market index returns. In the univariate regressions, the performance of the index is very strong. The adjusted R^2 provided by the index in 1-month, 3-month and 6-month regressions are 4.5 %, 4.9% and 7.1% respectively, which shows that the index performs really well in predicting the stock returns in the univariate setup, and in the short-horizon. The predicting power of the variable is an increasing function of the prediction horizon. The adjusted R^2 of the model is strictly increasing going from 1-month to 5-year horizon and the 5-year horizon's adjusted R^2 is equal to 41.6%. This is, to some extent, surprising as this variable is among the non-persistent class of predictors. This is based on the previous literature which emphasizes on the role of auto-correlation in the prediction power of the different predictors in the long-horizon.

We extensively test if the variable can survive the presence of other well-known stock market return predictors and if it stays significant after controlling for them. We do this in two different settings. One is to test the performance of the variable against the others in the short horizons. The results show that the variable is still a significant driver of returns, even after controlling for all of the other factors. We can also see that not only the variable is a significant factor in predicting the returns, but also, it makes most of the rival predictors of the stock market returns insignificant. The second setting is to test the prediction power in presence of other predictors in the long horizons. Again, in the long horizon, the index shows the ability to survive the presence of different well-known predictors of stock market returns.

One of the things which is important after we see the prediction power of a variable in-sample, is to test if it has the same performance out-of-sample. The importance of this is emphasized by different papers in the literature. Here, we do the out-of-sample performance test using expanding and rolling training windows with the length of 120 and 180 months.

The results show that the variable has an strong performance out-of-sample in the case that the length of the training window is 120 months. In the other cases, where the training window has the length of 180 months, the results are weaker. This can be due the short sample size that we have here. Later, we will propose a solution for this problem. All in all, it seems that the variable of ours is showing a considerable prediction power out-of-sample exactly like what it does in-sample.

The other question asked in our work is if the index we have calculated is a priced factor in the cross-section of stock returns. We have two different metrics for evaluating the fact if the factor is priced in the cross-section of stock returns. The first metric would be if we are having statistical significance for the Jensen's alphas in the regressions. The other one is to see if there is an increasing or decreasing trend in the average returns of the portfolios, going from the least-exposed to the most-exposed portfolio. We cannot see the presence of statistical significance in Jensen's alphas in our analysis, but we can detect an strictly decreasing trend in the average returns of the portfolios when we move from the least towards the most exposed portfolio. This can be an indicator that the factor is priced in the cross-section of stock returns.

We also investigate the determinants of our index and the relationship between the index and the major macroeconomic and fear indices. Among the most well-known macroeconomic and fear indices which can work as determinants, news VIX (NVIX) and its constituents are the ones which show the most significance for describing the variation in it. The total adjusted R^2 is equal to 32.1%. We also test the determinants of the index using multiple-variable setup, using different macro and uncertainty variables. The results show that the NVIX is still the most important determinant of our index, even in the presence of macroeconomic and uncertainty variables. The adjusted R^2 generated by this model is 39.6%.

We also investigate the power of the lags of our index for predicting main macroeconomic variables and the other disaster indexes proposed in the literature. The lags do a very good job in predicting NVIX index and its four lags predict NVIX with an adjusted R^2 of 30%. The index also has the ability to predict the policy uncertainty index by a high adjusted R^2 of 21.7%. Among the macroeconomic variables, the lags of our index has the highest power of prediction in the case of default spread and total consumption growth by providing 7.5% and 3.6% of adjusted R^2 respectively.

Finally, we want to investigate if we can interpret this index as a proxy for macroeconomic disaster risk. The method we use to investigate this effect is to see if our jump variable is a determinant of crash fear. For doing that, we need to have a proxy for the crash and macroeconomic disaster risk. The proxy we use in this paper is the slope of the implied volatility smile extracted from the index options. The results show that our index is a significant determinant of the slope for different levels of moneyness, both in univariate model where we only include the jump variable, and also in the bivariate setup where we control for the implied volatility of the at-the-money (hereafter ATM) index options as well.

As mentioned before, we do have a sample size restriction which makes us unable to test the performance of index in some cases, like the case of out-of-sample prediction. As a remedy to this problem we use some new data to augment the index. The main problem we had about the option-based index was that we only were able to come up with answers to questions using the data post-2004. The reason is that the index of ours is not showing enough variation before 2003 because of lack of deep out-of-the-money (hereafter OTM) options in the gold market. In order to augment our variable we use historical price of gold, orthogonalized by the time series of average price of precious metals. The way we augment our index is to gather the variation in the index and the new source of data. For this, we use the scores of the first principle component of the initial index and the new source of the data. Now we have data starting from 1990 instead of 2004. We run all the analyses we have done before using the new augmented variable. The results show that almost all the prediction power we had in the case of the option-based index can be seen here again. In addition, this index has a much better performance out of sample, as the sample size in this case is not an issue anymore.

II. Data and Methodology

The option prices on gold futures in this study are from CME (formerly known as NYMEX). The data for option prices is available from 1986 to 2020. There is an specific phenomenon and feature in commodity markets, specifically gold market, that needs to be mentioned here. Throughout the analysis in this paper, as will be described later, we will work with the OTM option contracts in the gold market. Figure 1 shows the total number of OTM options in gold market (call and put) from 1986 to 2020. As can be seen, there is an strictly increasing trend in the total number of OTM options from the beginning till the end of the sample. The other thing which is observable is that the number of OTM options at the beginning of the series is very small in comparison to latter part of it. This is due a phenomenon which is called the financialization of commodity markets. As a result of this process, the commodities is also an interesting asset class for portfolio investors, as it is the case about bonds and stocks. Based on the literature on the financial aspects of the commodity markets, the financialization of commodity markets have started around 2004. Looking at the figure, it is evident that the growth rate in the total number of OTM options is much greater in 2004-2020 sub-sample than the 1986-2003 sub-sample. Figure 2 is presenting the growth rate for the OTM call options, which are the used data in our analysis. The same trend and the greatness of the growth rate for the post-2004 sub-period which can be seen in the previous figure can be seen in this figure as well. Figure 3 shows the same concept through depicting the time series of the total open interest of the OTM call options throughout the whole sample. As we can see, the total open interest of the options is not even reported before 2005 by the CME. After this period, we can see the same pattern in the growth of the open interest of the OTM call options as the one seen in the previous two figures. Because our analysis is based on the availability of options for different strikes, the higher is the liquidity of options throughout the sample, the greater will be our precision. This is exactly why when we do our analysis, with the options data only, we would pick 2004 as the starting time of our sample. The last restriction goes back to what happened in 2020. The Covid-19 crisis has caused a peak in the time series of the jump variable in the gold market during 2020. Because we do not want the results of our analysis to be driven by outliers, we do not contain data from 2020 in the data sample used for our analysis. As a result, the main sample period used for our analysis based on the option-based variable is 2004-2019 sub-sample.

Bollerslev and Todorov (2011) show that if we assume F is the future price of the underlying at some future date, the absence of arbitrage would imply that the futures price should be semi-martingale. Then the dynamics of the futures price may be expressed as:

$$\frac{dF_t}{F_t} = \alpha_t dt + \sigma dW_t + \int\limits_R (e^x - 1)\,\widetilde{\mu}(dt, dx) \tag{1}$$

In order to better understand the impact and pricing of the two separate components, we can re-write the variation associated with the futures prices. Let QV represents the quadratic variation of the log price process over [t,T]. Then we will have :

$$QV_{[t,T]} \equiv \int_t^T \sigma_s^2 ds + \int_t^T \int_R x^2 \mu(ds, dx) \tag{2}$$

The right hand side of the equation consists of two terms. The first term represents the variation which can be attributed to the stochastic volatility process, or variation due to “small” price movements. The second term shows the variation due to jumps, or “large” price movements which are totally non-continuous. What is our main goal here is to quantify the risk-neutral jump in gold market which we will use as a measure of consumer panic or economic crash fear.

We can show that the risk-neutral expectation of total quadratic variation, normalized by horizon T-t, can be written as:

$$QV_t^Q \equiv E_t^Q(\int_t^T \sigma_s^2 ds) + \frac{1}{T-t} E_t^Q(\int_t^T \int_R x^2 \mu(ds, dx)) \tag{3}$$

This shows that the total quadratic variation and its components both can be estimated using an array of option contracts with different strike prices. The basic idea that we are using is that a deep OTM option can only be in-the-money (hereafter ITM) in very short term if an unexpected jump which is non-continuous and non-diffusive happens. The paper proposes the following equations and methodology to measure the risk-neutral jump tail measures as:

$$RT_t^Q(k) \equiv \frac{1}{T-t} \int_t^T \int\limits_R (e^x - e^k)^+ E_t^Q(\nu_s^Q(dx))ds \approx \frac{e^{r(t,T]} C_t(K)}{(T-t)F_{t-}} \tag{4}$$

$$LT_t^Q(k) \equiv \frac{1}{T-t} \int_t^T \int\limits_R (e^k - e^x)^+ E_t^Q(\nu_s^Q(dx))ds \approx \frac{e^{r(t,T]} P_t(K)}{(T-t)F_{t-}} \tag{5}$$

Where RT and LT are showing the right and left risk-neutral jump tail variation respectively. Once more, we should emphasize that the main implication of the methodology is that if we have a set of deep OTM option contracts on a specific underlying, then the only price movement which can change the options to ITM options in short-term is big and discontinuous price movements (jump). As a result, the prices of deep OTM options with very short time to maturity can be used in order to quantify jump and differentiate it from diffusive process.

So far, we have established the fact that the OTM call options with short maturity in gold market have the power to capture the jump component. The gap in the methodology described above is that the authors of the paper decide about the threshold at which jump and diffusion components will be separated from each other and then pick the option contract closest to that threshold and its price as a measurement for the jump component we are looking for. The question we can, and we will, ask here is why should we only consider a single option and not a continuum of call option prices. In order to do something like that, we have to come up with a methodology that can utilize whole options data we have across different strike prices. Actually, the methodology is available and is widely used in different papers in the literature of asset pricing in finance.

The main obstacle on the road is that we do not have equal length of moneyness for OTM call options for all the days in the data. Also, we do not have a continuum of options which helps us to calculate the index every single day. To conquer this problem we will use the methodology proposed by Trolle and Schwartz (2010). First, we need to pay attention to the fact that the option contracts we do work with are all American options on futures contracts. If we want to work with regular techniques in asset pricing and finance, we need to do the calculations based on the prices of European option contracts instead. The first step here is to calculate the implied volatility of the options using the Bjerksund and Stensland (2002) approach. The next step is to go from non-continuous implied volatility to continuous implied volatility for the options contracts. This will be done using linear interpolation. For an option with strike K, having the log-normality assumption of Black (1976), the moneyness will be calculated as:

$$d = \frac{\log(K/F(t,T_1)}{\sigma\sqrt{T-t}} \tag{6}$$

Where K is the strike price, F is the futures price and σ is the implied volatility of the ATM options.

We want the continuum of implied volatility of option contracts from d=-10 and d=10 which is equivalent to having the continuum of implied volatility for options between strike prices $K_{\min} = F(t,T_1)e^{-10\sigma\sqrt{T-t}}$ and $K_{\max} = F(t,T_1)e^{10\sigma\sqrt{T-t}}$. But, we are still far from getting to the point that we can calculate the measure that grasp the jump component, because the measure is based on the prices of European option contracts. Using the continuum of implied volatility of the options and with the help of Black (1976) option pricing model, we will convert the series of implied volatility we have into a series of European options prices. We also do flat extrapolation for strike prices less than $K_{\min}$ and greater than $K_{\max}$. Now that we have the continuum of prices, the only thing which is remained is to pick the threshold beyond which we want to include the option prices and before which we want to discard the data. In this case we use the threshold of $K = F(t,T_1)e^{4\sigma\sqrt{(T-t)}}$. The measure we use here is the integral over the prices of all OTM option contracts in gold market with strike greater than or equal to our threshold. The reason why we are choosing this specific threshold is twofold. First, we want to capture big jumps. Secondly, we have tested multiple thresholds from σ to 4σ and the latter gave us the best predictability results among all the measures. We call this index the Gold Risk Neutral Jump, hereafter $GRNJ$.

As discussed, because the deeper OTM options protect investors against large price changes, the strategy above can be reflecting the expectations of the investors about huge price increases in gold futures. As can be seen, our measure combines all the OTM call options with different moneyness levels with strikes greater than the threshold. In fact under no arbitrage conditions the measure is nothing but disaster insurance against very big jumps in the price of gold for investors.

The series of options we use at each day are option contracts on gold futures with minimum days of maturity of 8 days. The filters applied to the options data are standard filers by Trolle and Schwartz (2010). We have deleted option contracts with prices less than 0.05 \$ and with open interest less than 100.

Figure 4 depicts the daily time series of GRNJ. There are very interesting facts that can be inferred from the time series. The time series shows a considerable amount of variation around some big credit and economic crises times like the Asian financial crisis in the late 90s, the global stock market downturn in 2002, the big financial crisis of 2007-2008, the US debt downgrade and Euro debt crisis in 2011 and also the Covid-19 crisis of 2020. One of the other signs that the GRNJ is able to track financial crises is that the index has very different behavior in the two sub-periods of of 1986-1998 and 1998-2020. The series is much more volatile during the second sub-period. This is intuitive as most of the big financial crises that we earlier mentioned took place during the this sub-period. The last observation about the time series of GRNJ is that our index fluctuates around the time of some of the major geopolitical events and wars. The first Persian Gulf war of 1991, the 9/11 attacks, the military invasion of United States to Iraq in 2003 and the Israel and Lebanon war of 2006 are some of the incidents that show the GRNJ index is sensitive to geopolitical matters in addition to financial matters and crises. Figure 5 is showing the times-series of the index excluding the Covid-19 crisis. Because we do not want our results to be run by a single outlier observation, we only use the data up to the beginning of 2020 in this study and do not take the Covid-19 period into account. One of the problems of working with daily data is that the data is noisy at this frequency most of the time. Because of this problem and also based on the convention in return prediction literature we do transform the data from daily to monthly data. We do this by taking the average of the daily sample over the days of each month. Figure 6 is showing the monthly data. We can see that the data still shows the peaks during the recessions and macroeconomic problems, like the ones picked as recession periods by the NBER, which are the shaded areas in the graph.

The measure of U.S. stock returns used here is the CRSP value-weighted index. LogGP ratio is from Huang and Kilic (2019). The Gold and Platinum prices are the monthly average of daily prices from London Bullion Market Association (LMBA) and London Platinum and Palladium Market(LPPM). The logGP variable is calculated as the natural log of the gold over platinum prices. The risk-free interest rate is proxied by effective federal funds rate.

Table I contains the summary statistics for all the predictors in this study. the AR(1) coefficients are reported in column three of the table. The coefficient shows that, with the exception of GRNJ and VRP, the rest of variables are highly persistent. From the augmented Dickey-Fuller test statistic and associated p-value which is reported in the fifth column, we can easily verify that the AR(1) coefficient of our predictor is inside the unit circle and the null hypothesis of having a unit root, and as a result non-stationarity, can be rejected. It is worth paying attention to the fact that this is not the case for the rest of the predictors we are trying to compare ours to. The AR(1) coefficients and their p-value of their unit-root test shows that most of them are very persistent and we cannot reject the null of non-stationarity in their cases. This is important because in the next sections we try to test the ability of different variables in predicting returns across different horizons. When doing that, we would expect to see that the higher is the level of persistence in a predictor, the higher is going to be its ability to predict returns in long horizons. At many times, this is not because there is a high ability in the predictor to predict the returns based on its information content, but it is only the matter of persistence. We will discuss this point more meticulously in the next sections. $\log PD$ is the log price-dividend ratio from the CRSP value-weighted index. $\log PNY$ is the log of net payout yield from Michael Robert's website. CAY is the consumption-wealth ratio and it is from Lettau and Ludvigson 2001. The data is coming from Martin Lettau's website. $DFSP$, which is default premium, is the difference between the yield of the Baa and Aaa corporate bonds and it is taken from FRED's website. $Inflation$ is the growth rate of consumer price index (CPI) and it is also given from FRED's website. $TMSP$ which is the abbreviation for term spread is the difference between the yield of a 10-year constant maturity U.S. government bond and a 3-month constant maturity U.S. treasury bill. The data is taken from FRED. $\log PE$ is the cyclically adjusted price-earning ratio from Robert Shiller's website. VRP is the variance risk premium, the difference between risk-neutral and physical variance in stock market, taken from Hao Zhou's website.

Alongside of the stationarity of GRNJ, we can talk bout another aspect of the data in this table. Column eight of the table is showing the correlation between GRNJ and other variables. Among all, the correlation of GRNJ with variables which are the indicators of the overall health of the financial markets is interesting. The correlation of GRNJ with logPE is -0.67 and the correlation between GRNJ and logPD is -0.66. This is an indicator that our variable moves in the opposite direction of the the two indicators. This is a piece of evidence that GRNJ variable is counter-cyclical. Looking at the macroeconomic variables which are the indicators of chaos and financial distress, we can see that the correlations between these variables like DFSP, TMSP and GRNJ are positive. This is another indicator which shows that the variable of interest in this study is a counter-cyclical variable.

III. Results

A. Stock Return Predictability Univariate

We will investigate the prediction power of GRNJ for predicting stock returns using the following regression:

$$\frac{12}{h}\sum_{i=1}^{h}\log R_{t+i} - \log R^f_{t+i} = \beta_0 + \beta_1 GRNJ_t + \varepsilon_{t+h} \tag{7}$$

It would be beneficial if we discuss the regression equation. As mentioned before, the final data that we work with is in monthly frequency. What we want to do here is to not only to test the prediction power of our variable at the monthly horizon but also the prediction power in the longer horizons, up to five years. In order to come up with the data to do the long-horizon regressions, we use overlapping monthly returns. The last thing to mention is that the overlapping monthly returns method enables us to have the same number of observations for our monthly regression as the regressions based on longer horizons. In the equation above, h is the number of months. As a result, the left hand side of the equation is the annualized excess returns for the horizon of h months. Table II shows the results of the univariate predictability least squares regressions with Newey and West (1987) HAC robust standard errors. At the 1-month horizon the degree of predictability is considerable with adjusted R^2 equal to 4.5%. We can see that the variable is still a significant predictor of returns at the 3-month horizon. The adjusted R^2 for this prediction horizon is equal to 4.9% and the coefficient of the predictor is still significant at the confidence level of 99%. The increasing trend of the adjusted R^2 of the predictive regressions can be seen moving from 3-month to 5-year horizon. The adjusted R^2 for the 6-month, 1-year, 2-year, 3-year, 4-year and 5-year horizons are 7.1%, 11.3%, 22%, 31.3%, 38.2% and 41.6% respectively. Earlier, we discussed that the variables which have the greatest level of persistence are the ones which show the highest prediction power in the long horizons. We also mentioned that this phenomenon can be seen in the case of these variables because of their persistence not because of the information content of the variables. Our variable is able to strongly predict the returns in the long horizons although it is not a persistent variable. This shows the prediction power coming from information content of GRNJ.

Table III is presenting the results which can help us to compare different variables in the study in terms of both their power for predicting the returns (adjusted R^2) and statistical significance of the variables in this procedure. The first two columns of the table are showing the results for the short-horizon cases and the last two columns are presenting the results for the case of long-horizon predictions. In the 1-month horizon, the GRNJ is statistically significant and is showing 4.9% of adjusted R^2. The only other significant variables for this horizon are logGP, CAY and VRP. The adjusted R^2 of the three variables are respectively equal to 1%, 2.9% and 7.6%. The rest of the variables are not showing any statistical significance at this horizon. We can verify that the only variable which is providing higher adjusted R^2 than our GRNJ variable is variance risk premium which is historically known as a strong variable for predicting stock market returns in the short horizons. The next horizon to look at is the 3-month horizon. In this horizon, the only significant variables are GRNJ, logPE and VRP. The adjusted R^2 of these three predictors in their univariate regressions are respectively 4.9%, 2.9% and 9.8%. The adjusted R^2 for GRNJ is the second largest one among all in this table. This shows that there are only few variables, known in the literature as the stock market return predictors that are actually able to predict the returns in short horizon. Among those, it seems GRNJ which is introduced for the first time in this paper, is among one of the most significant and powerful predictors of stock market returns. The last two columns of the table are showing the results for the case of long-horizon predictability. Looking at the results in column three we can see that there are multiple significant variables in the 1-year horizon. GRNJ still seems to be a variable with statistical significance and it is providing an adjusted R^2 of 11.3% at this horizon. The only variable which is providing an adjusted R^2 greater than this amount is logGP variable which is providing an adjusted R^2 equal to 18%. Again, logGP is among the most persistent variables in our sample. The VRP which is one of the most non-persistent variables and works very strongly in shorter horizons is not showing statistical significance at this specific horizon. The GRNJ variable is still a significant and powerful predictor of stock returns in the 5-year horizon and shows one of the highest adjusted R^2 among all the variables. All in all, it seems that GRNJ is one of the strongest predictors of stock market returns in the univariate setting and in comparison with other well-known predictors in the literature.

B. *Stock Return Predictability-bivariate*

The question we want answer in this section in the following: How does GRNJ index work as a predictor of returns in comparison to other predictors, in a horse race? To answer this question we initially need to modify our regression model. The new model will look like:

$$\frac{12}{h}\sum_{i=1}^{h}\log R_{t+i} - \log R_{t+i}^{f} = \beta_0 + \beta_1 GRNJ + \beta_2 X_t + \varepsilon_{t+h} \tag{8}$$

Where X is the predictor other than GRNJ that we want to investigate the effect of its presence. We put the rival predictors one by one in the model and see if their presence is going to weaken statistical significance of the GRNJ variable. Table IV is presenting the results of all the bivariate regressions for the short horizons of 1 month and 3 months. The results for the short-horizon analysis shows that not only the GRNJ variables is a significant predictor in presence of all other variables in the analysis, but also the inclusion of this variable is going to make most of the other rival variables insignificant. The only variable which is keeping its significance throughout the regressions is the VRP. As mentioned before, VRP is one of the most prominent predictors of stock returns in the short horizon. Even in the presence of VRP, the prediction power of GRNJ is intact. The only variable which is able to reduce the significance level of the GRNJ from 95% to 90% is logPD. For the 3-month horizon, the variable is going to make the impact on the significance level of the GRNJ variable. The size of the coefficients for GRNJ in the regressions and also the sign of the coefficients are stable across different models and regressions. The sign is always positive and the magnitude is around 0.006 for the case of 1-month horizon and 0.004 for the case of 3-month horizon.

Table V is presenting the results for the case of long, 1-year and 5-year, horizons. We will concentrate on the results for the 1-year horizon first. Among all the variables that we have included in this horse race, the only one which can reduce the significance level of our GRNJ variable from 95% to 90% is the logGP variable. In the case of the rest of the rivals, not only they are not able to reduce the significance level or impact the sign of the coefficient of GRNJ, but also they are not showing any statistical significance themselves. It is an interesting fact because we know, from the papers in the literature, that these variables are mostly significant predictors of stock market returns in the long horizon because of their high persistence level. This is therefore an indication of the power of our variable in terms of predicting stock market returns in the long horizon, exactly like the case of the short horizon. The last case we want to take a look at within the framework of bivariate prediction power is the case of 5-year horizon. The second column of the table is presenting the results for this specific case. As we can see from the table, our variable, GRNJ, is still a fully-significant predictor of stock returns across different regressions and after inclusion of different variables. Although most of the rival predictors are statistically significant at this horizon, they are not having any effect on the significance of our variable. The sign of the coefficients related to GRNJ are also stable and positive across different specifications.

All in all, we can conclude that our GRNJ variable is a robust, significant and powerful predictor of stock market returns, both in the short and long horizons. The inclusion of none of the rival variables, either in the short or long horizon, will affect the significance and magnitude of the coefficient of our GRNJ variable in different regressions. Also, as seen, most of the variables do not survive the presence of GRNJ in the specification and lose their significance after its inclusion. The only case which the rival predictors are significant along with GRNJ is the case of very long horizons (5-year horizon).

C. Out of Sample Prediction

Goyal and Welch (2008) is one the most cited papers in the literature which points out the deficiency of classic predictors of stock market returns when they are used out-of-sample instead of in-sample. In this paper, we build a standard type of out-of-sample R^2 and judge the robustness of the out-of-sample performance of GRNJ using the index. If we have GRNJ as a robust predictor out-of-sample, like it is in-sample, we should see that the R^2 is is significantly different from zero (positive) and close to the R^2 we have derived in the case of in-sample analysis of the data. The test statistic that we use in this stage has the following form:

$$R^2_{OS} = 1 - \frac{\sum_{k=1}^{T-m} \left(r^e_{m+k} - \hat{r}^e_{m+k}\right)^2}{\sum_{k=1}^{T-m} \left(r^e_{m+k} - \bar{r}^e_{m+k}\right)^2} \tag{9}$$

There are two different methods using which we calculate R^2_{OS}. The two are rolling window and expanding window approaches. The thing which is common across both approaches is that we estimate equation (7) in a period which we call estimation period, then we do calculate the square of prediction error over the next period and we increment our step. Among the two approaches the rolling window has a greater ability in capturing the change in the predictive relationship through time while the expanding window approach has the advantage of better usage of the available data. In the literature, the standard length of the windows used for this analysis is 120 and 180 months. These are the periods which using its data we train our model. Then, we try to predict the return in the subsequent period. Clark and West (2007) propose an adjusted-MSPE statistic with the form:

$$f_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - [(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2] \tag{10}$$

The statistic will be regressed against a constant and we will use a one-sided test to see if $R^2_{OS}>0$.

Table VI shows the results from the analysis we have done out-of-sample. The p-value for each of the calculated statistics is reported in the table, in the column next to the column containing the statistic's value. We can see that the magnitude of the out-of-sample R^2 is generally increasing going from 1-month towards 5-year horizons, both in the case of 120-month expanding and 120-month rolling predictive regressions. The situation is slightly different in the case of both expanding and rolling predictive regressions when we use a

180-month training window for our analysis. The trend in the magnitude of the statistics in the cases of 180-month rolling and expanding windows is increasing in the beginning but decreasing in the middle and the end. Also, we can see that the R^2 statistic for the case of expanding window with initial length of 180 months is negative and statistically significant at the 5-year horizon. It is highly probable that this is due the sample size problem. The whole data points we have available for this analysis are 192 points, while we are using 180 of them for training the model. For this reason, later in the following sections, we try to expand the sample size using the data available on the price of precious metals historically. In sum, the results show that GRNJ is a powerful out-of-sample predictor of stock returns.

D. GRNJ and the Cross-Section of Stock returns

According to the ICAPM, if GRNJ is priced factors in the cross-section of stock returns, then the returns on stocks should depend on their sensitivities to its innovations. In this section, we would test whether GRNJ is a priced factor in the cross-section of stock returns. Ang, Hodrick, Zhing and Zhang(2006) show that the higher is the sensitivity of a stock to innovations in market volatility, the lower is the average return of the stock, using the data in NYSE/AMEX/NASDAQ between 1990 to 2012. Our approach is related, but somewhat different, in that we use sensitivity to innovations of GRNJ. The first element needed for this kind of exercise is to calculate the innovations in GRNJ. We do measure the innovations by the difference between the real data points and predicted values by an AR(1) model.

Following Ebrahimi and Pirrong (2018) and Christofferson and Pan (2015), we use daily returns on NYSE, AMEX and NASDAQ stocks and a 30-day estimation window in order to estimate time varying factor exposures. At the end of each month, we run the following regression for each of the stocks in the sample to get the sensitivity of the stock's return to the innovations in GRNJ :

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{GRNJ_{innov}} GRNJ_{innov_t} + \varepsilon_{i,t} \tag{11}$$

At the end of each month, we sort all stocks in the data based on the estimated sensitivities to the $GRNJ_{innov}$, measured by $\beta_{GRNJ_{innov}}$. We then form five portfolios of the sorted stocks, portfolio one having the lowest and portfolio five having the highest exposure to $\beta_{GRNJ_{innov}}$. We then calculate the time series of post-ranking returns of each of these five portfolios during the following 30 days. Each month, we roll the window for one month and repeat this procedure through the sample period. This procedure produces daily returns for the five portfolios during the sample period.

We next estimate the following regression on the daily return data:

$$R_{p,t} - R_{f,t} = \alpha^p + \beta^p_{MKT}(R_{m,t} - R_{f,t}) + \beta^p_{SMB} SMB_t + \beta^p_{HML} HML_t + \beta^p_{UMD} UMD_t + \varepsilon_{p,t} \quad (12)$$

where $R_{p,t}$ is the return of each portfolio, SMB and HML are the Fama-French (1993) size and value factors respectively, and UMD is the momentum factor from Carhart (1997). Statistical significance of the α^p implies that the factor is priced in the cross-section of stock returns.

Table VII reports the average pre-ranking βs, the Jensen's α, and the average post-ranking monthly returns in the case of $GRNJ_{innov}$. In this table, we report the p-value of Jensen's α calculated using Newey-West standard errors with 21 lags. Columns one to five present the results for five sorted portfolios, portfolio 1 having the lowest and 5 having the highest exposure to $GRNJ_{innov}$. We also report the average return and the Jensen's α for the portfolio that longs the highest exposure quintile portfolio and shorts the lowest exposure quintile of stocks. Results for this strategy are reported in column six, labeled "5-1". The average monthly Jensen's α is the estimated intercept multiplied by 21 to report a monthly value.

As noted before, we try to answer the question of if the factor is priced in the cross-section of stock returns or not from two different lenses. One of them is the possible trend in average post-ranking returns of the five portfolios. The other lens through which we look at this problem is to investigate if the Jensen's alpha generated by this procedure is statistically significant at the 95% confidence level or not. Looking at the table we can see that the statistical significance of the Jensen's alphas is not present in this case, as none of the p-values are less than 0.05. However, if we look at the average returns of the five portfolios, moving from portfolio one which is the least exposed portfolio towards portfolio five which is the most exposed portfolio, we can see that there is clear downward trend in the average returns of the portfolios. Although we do not have the case of statistical significance of Jensen's alphas here, we can conclude that the GRNJ is a priced factor in the cross-section of stock returns.

E. Determinants of GRNJ

Now that we are aware of the power of GRNJ in predicting stock market returns, it would be really helpful if we can investigate the determinants of the index. For this purpose, we gather two class of variables which might be relevant to the variation inside our variable of interest. The variables we consider as the potential determinants of the GRNJ are worth to be described briefly. $NVIX$ is the news VIX index by Manela and Moreira (2016). This is a text based measure which has been created out of looking for some macro and fear-related words in the front page articles of newspapers for a long period of time. The data is available at the daily frequency. The NVIX has different components which classifies the fear toward the situation of the economy into fear about stock market, fear about a war happening in the future, etc. The $SecuritiesMarkets$ is the variable which is measuring the level of panic about the future of securities markets and it is one of the several parts of NVIX. Table VIII shows the results of contemporaneous regressions of GRNJ on the constituents of NVIX. As we can see, almost all the constituents of NVIX are statistically significant when we run GRNJ as the dependent variable and each of these parts as the independent variable in a regression. The only case under which there is no statistical significance is the case where the independent variable is the $NaturalDisaster$ part of NVIX index. In terms of adjusted R^2, again, all parts of the NVIX, other than the natural disaster, are generating considerable amount of adjusted R^2. Finally, we can see that the NVIX itself is an statistically significant variable with a very high adjusted R^2 of 32.1%. The established relationship between the NVIX and the GRNJ is very important. As discussed, NVIX is a measure of macroeconomic disaster risk. The relationship between this variable and GRNJ index shows that our variable works fine as a proxy for disastrous situation of the macroeconomy and as a result as a crash fear index.

The second class of determinants at which we want to look in this part of the study are macroeconomic and uncertainty variables. Policy Uncertainty Index, which is shown by PUI, is another text-based index which measures the uncertainty about policy-making. The index is proposed by Baker et al. (2016) and it is available for different countries. Here we only use the policy uncertainty index which is related to the United States. $TedSpread$ is the difference between 3-month treasury rate and 3-month libor rate. ΔIP and $\Delta IPMAN$ are respectively growth in industrial production and the manufacturing component of industrial production. ΔPCE is the growth in personal consumption expenditure. The data is available at monthly frequency and we use it as a measure of overall consumption growth. $DFSP$ is the default spread which is the gap between the yield of the Aaa and Baa bonds from FRED.

Table IX is presenting the results of a contemporaneous regression of GRNJ on all of the variables mentioned above. As we can see, the only variable which can be seen to have significant relationship with GRNJ is NVIX. In other words, in presence of NVIX, the other macroeconomic variables are not having a significant relationship with GRNJ. The signs of the coefficients estimated is as expected. Also we can see that the regression is showing considerable adjusted R^2 of 39.6%. This is a very interesting result. In fact, what we got means that the only variable which have contemporaneous relationship with GRNJ is the one which is representing the possibility of a disaster happening through the financial sector. Once again, we can verify that GRNJ can be used as a measure of macroeconomic disaster.

F. Predicting Macro and Financial Variables

In this section we want to investigate if GRNJ lags are able to predict macroeconomic variables and most well-known financial fear indexes in the literature. There has been a vast literature about how the prices of commodities impact macroeconomic variables. (Hamilton (1996), Hamilton (1983), Kilian (2017), Céspedes and Velasco (2012) etc.) However, there is a thin literature about the ability of option-based measures from commodity markets in predicting macroeconomic variables. Tables X and XI show the result of our attempt to investigate the prediction power of the variable using the first four lags of it. Also, figure 7 is presenting the impulse response functions (hereafter IRF) which shows the response of variables to shocks to GRNJ. Table X shows the result for the first five variables we have picked among macro and fear factors. The first factor to look at is the NVIX factor. The results show that the coefficient associated with the first lag of the GRNJ is statistically significant and its sign is also positive. It means that the higher value for the fear factor in gold market translates into having a higher overall fear perception in the financial markets and the economy.

The second variable under investigation in this section is the securities markets component of the NVIX. It is important for us to know if the predictability evidence that we got for the case of NVIX is coming from the predictability of the securities markets component of the NVIX or the other components of it. What we got as a result of running the regressions in this case can verify the fact that the predictability of NVIX by GRNJ can be tied to predictability of the securities markets component of NVIX, to a small extent. Only the last (forth) lag of $GRNJ$ index is statistically significant and also positive, meaning that an increase in the GRNJ will cause an increase in the securities markets component of the NVIX. The adjusted R^2 provided by the model is equal to 4.9%. The results show that there is a big part of predictability of NVIX which cannot be explained by the predictability of the securities markets component of NVIX. The IRF which shows the effect of shocks to GRNJ on the securities markets component of the NVIX show that once the shock happens the level of securities markets is going to go up. In the medium term, the effect is going to get smaller. In the long term, as expected, the effect of GRNJ on the securities markets component is going to die. The IRF is within the statistical bounds all the time, meaning that the relationship between two variables remains statistically significant throughout the time frame we are looking at.

The third column of the table is dedicated to the regression of policy uncertainty index on the GRNJ's lags. Our anticipation is that the higher GRNJ will be translated into the higher policy uncertainty index in the United States' economy. The results show exactly the same thing. In contrast with the second and third lags of the variable which are not statistically significant at the 95% confidence level, lags one and four are significant with positive sign. This means that an increase in the level of GRNJ will cause an increase in the overall level of policy uncertainty index in the United States. The fact that the statistical significance for the fourth lag shows the persistence in the relationship between shocks to GRNJ and the value of the variable. The IRF function for the effect of shocks to $GRNJ$ on the policy uncertainty index can verify all mentioned above. It seems after a shock, the value of the policy uncertainty index goes up in the short run. After that, there is a decrease in the value of policy uncertainty and then the effect of the policy uncertainty goes towards zero. We can easily see that the effect of shocks to the GRNJ variable in the case of policy uncertainty index dies slower than the previous cases and variables.

Column four shows the results for the case that we are trying to predict the $Intermediation$ component of NVIX by the lags of GRNJ. The results show that the first two lags of the GRNJ are positive and statistically significant. Lags three and four are not showing any statistical significance at the 95% confidence level. Also the adjusted R^2 of the multi-variate predictive regression in this case is 7.1% which is stronger than the other part of the NVIX which we looked at before. All in all, we can see that the lagged model we are using to predict intermediation component is considerably powerful.

Column five shows the results for the regression of Industrial Production growth on four lags of GRNJ. Our prior for industrial production growth and its relationship to GRNJ is that the higher values of GRNJ, which is an indicator of financial distress, will increase the possibility of the economy entering a new recession. As a result, the higher is the GRNJ index, the lower is expected to be the industrial production growth. The results show that the relationship between the lags of GRNJ and industrial production growth is not significant. Although the sign of the first three lags of the predictive variable are negative, based on expectations, there is no statistical significance for these lags. Also, the overall adjusted R^2 of the model is weak, even negative. The IRF though shows exactly the things we expected. As a result of a positive shock to GRNJ, the growth in industrial production goes negative in the short run. In medium and long term, it seems that the effect of shock to GRNJ weakens and converges to zero.

The rest of the regression results in this section are gathered in table XI. Column one is showing the results for the case of VIX and its relationship with the lags of GRNJ. As we know, VIX in nothing but another option-based fear index. The main difference between the VIX and indices like GRNJ is that the VIX is calculated based on the out-of-the-money options on S&P 500 index, while GRNJ tries to capture the fear through calculations based on some non-index out-of-the-money options, here gold options. As a result, we exactly know what our prior about the relationship between GRNJ lags and VIX should be. Logically, there should be a positive relationship between GRNJ and VIX. The results in the column shows that our prior matches the reality of the relationship between the two variables. The coefficient for the first lag of GRNJ is positive and statistically significant at the conventional 95% confidence level. Also, we can see that the absolute value of the coefficients goes down, going from lag one to lag four. This can be an indicator that the effect of the shocks are going to diminish as time passes by.

The next variable that we are looking at here is the Aruoba-Diebolad and Scotti (2009) index or *ADS*. ADS is an index for business conditions and can be used as a gauge of macroeconomic health level. As a result, we expect the variables which are indicating economic problems to have a negative relationship with the ADS. In fact the higher is the ADS, the lower is the possibility of the economy entering into another imminent recession, so we expect the relationship between ADS and GRNJ's lags to be negative. Although the first three lags of GRNJ have negative coefficients and the trend in their absolute value going from lag one to lag three is decreasing, we cannot see a clear prediction power from the side of the GRNJ for the ADS variable. The adjusted R^2 of the regression is negative which is a confirmation of the inability of the lags of GRNJ to be a powerful predictor of the ADS index.

The results for the default spread (DFSP) are presented in the column three of the table. The default spread is nothing but the difference between the yield of the Baa and Aaa rated corporate bonds. As a result, we expect default spread to be an increasing function of GRNJ . What happens is that when the crisis emerges in the economy, the gap between the yield of two different type of bonds gets wider and wider. The results show that the coefficients on the first two lags of GRNJ are positive and statistically significant. This is in-line with all the expectations we had before running the regressions.

The next variable of interest to investigate the effect of changes in GRNJ lags on is IPMAN growth. Based on the prior discussions, we expect the relationship between the lags of GRNJ and this variable to be negative. The reason is that the IPMAN growth should be negative in the times that the risk and the possibility of entering into a recession goes up. Although the results are showing the coefficients of the first three lags of GRNJ are negative, the lags are not statistically significant. The IRF contains a very interesting pattern of the relationship between these two variables. The level of IPMAN growth goes down as a result of positive shock to GRNJ in the short term. In the medium term the negative effect gets even bigger than before. In the long term, the effect of the shocks to GRNJ on the IPMAN growth diminishes more and more and converges to zero.

The last variable we investigate in this section is PCE growth. One of the signs of recession in the U.S. or any other country is that the level of consumption will decrease drastically. As a result, we expect the relationship between an increase in the level of GRNJ's lags and PCE growth to be negative. The results show that first lag of the GRNJ has a negative coefficient and is statistically significant at the conventional 95% level. This is exactly what we expected before running the regressions, based on the theoretical relationship between the two variables. The IRF related to PCE growth shows that the level of the consumption goes down dramatically as a result of the shock to GRNJ in the short term. In the medium term, the effect of the shock to GRNJ gets smaller and in the long term, there is almost no effect from the shocks of GRNJ on the consumption growth.

G. GRNJ and Tail Risk

So far, we have gathered the following evidence : 1) GRNJ is counter-cyclical and it shoots up in the time of macroeconomic downturn and financial distress 2) GRNJ positively predicts stock market excess returns 3) GRNJ is having a positive relationship with the default premium and NVIX and a negative relationship with consumption growth 4) GRNJ is priced in the cross-section of stock returns with a negative price of risk. One of the ways which is plausible to interpret these results is that the GRNJ is an indicator of the market tail risk. In this section, what we do is that we extract the tail risk measure for the whole economy using option contracts on market index, and then investigate the implications of the GRNJ for the tail risk.

We know that the OTM options protect the investors against market crashes and macroeconomic disasters. Based on Pan (2002), we can measure the tail risk from option contracts by calculating the slope of implied volatility smile. This slope can be calculated using the difference of the implied volatility of OTM put option contract and ATM put option contract which have the same time to maturity. For calculating the index, we would follow Huang and Kilic (2019). We take the implied volatility of the OTM index options from the OptionMetrics and we define the slope as the difference between the implied volatility of OTM put options between 20Δ and 40Δ, and the implied volatility of the at-the-money option which is the nearest one to 50Δ. The related regression for doing our analysis would be:

$$\underbrace{SLOPE_t^{\Delta}}_{\sigma_{t,IV}^{OTM,\Delta}-\sigma_{t,IV}^{ATM}} = \beta_0 + \beta_1 GRNJ_t + \beta_2 \sigma_{t,IV}^{ATM} + \varepsilon_t \tag{13}$$

We add $\sigma_{t,IV}^{ATM}$ to take into account the level of implied volatility. Table XII presents the results for this case. As we can see, GRNJ is an statistically significant variable at the 90% level for all the levels of moneyness and the adjusted R^2 of the regressions are increasing when we go towards the case of the deeper OTM put options. This is a clear indicator that GRNJ is a solid measure of tail risk in the financial markets.

H. Extension

In the first section of the paper, we discussed that there is a shortcoming in the options data in the realm of commodities. The measure we built is based on the very deep OTM options, while the deep OTM options are only present in the post-financialization period of the commodity markets, which is essentially the period after 2004. As can be seen in figures 4 and 5, the dynamic of GRNJ before and after this point of time is very different and the index is showing much more volatility and dynamics after the start of the financialization period. This is the reason why the whole analysis we have done so far is based on the post-2004 data. Also, we saw that some of the exercises that we wanted to do in the previous sections, like checking the out-of-sample performance of GRNJ, was not possible to be done in full extent because of the shortness of the sample we had in hand, after 2004.

Because of all these reasons, we try to use a new source of information to augment the GRNJ index and make the time series of a new index, using which we can test different things we were not able to test before. For doing this, we will utilize the prices of different precious metals we have in hand. As discussed in the beginning, gold is mainly used for three purposes of making jewelry, production and storing the value of wealth as a safe haven asset. The other precious metals, here we wok with the most important ones palladium , platinum and silver, are used mainly for production purposes or making jewelry. So, one of the ways that comes to mind is something similar to what Hung and Kilic (2019) does to isolate the safe haven channel. In the mentioned paper, the authors use the fraction of gold price over platinum price as a proxy for the safe haven channel. We do something similar, but somewhat different from them. Logically, if we have a time series for the price of gold and another time series for the average prices of precious metals (including gold itself), taking the variation of the latter out of the former, we will have a proxy for the safe haven demand channel. Figure 8 shows the two time series of interest.

The way using which we want to take out the variation of the average prices time series from the gold time series' variation is to run a regression of the latter on the former series and take the residuals as the measure of interest. Figure 9 is showing the residuals of the mentioned regression. As we can see the measure is showing a considerable pattern of volatility throughout the whole sample time and also peaks during the NBER recession periods which can be seen in the figure as shaded areas. This is a sign that the residuals are showing the safe haven channel characteristics.

At this point, we have access to two time series. One of them is the residuals of the regression of gold price on average prices of preciuos metals and the second one is GRNJ. The most well-known technique for combining the variation of different variables is Principal Component Analysis. We run the principal component analysis on the two time series and pick the time series of the scores of the first principal component and call it PC. Figure 10 is presenting the time series of the PC variable. As we can see, the variable is showing a considerable amount of variation throughout the sample. The time series also peaks during the NBER recession periods. Now we have a time series which is available from 1990 all the way to 2020 and we can do all the analyses, including the out-of-sample performance test, using this new time series. The rest of the paper will essentially repeat all we have done already using the new predictor, PC, instead of GRNJ, and with bigger sample size. In fact, the rest of our analyses will be based on the 1990-2019 instead of 2004-2019.

I. Stock Return Predictability Univariate

Table XIII shows the main predictability results of our paper, based on the PC index. The main regression for this section is the following:

$$\frac{12}{h}\sum_{i=1}^{h}\log R_{t+i}-\log R^{f}_{t+i}=\beta_0+\beta_1 PC_t+\varepsilon_{t+h} \tag{14}$$

At the 1-month horizon the degree of predictability is considerable with adjusted R^2 equal to 2.4%. We can see that the variable is still a significant predictor of returns at 3-month horizon. The adjusted R^2 for this prediction horizon is equal to 7.1% and the coefficient of the predictor is still significant at the confidence level of 99%. The increasing trend of the adjusted R^2 of the predictive regressions can be seen moving from 3-month to 5-year horizon. The adjusted R^2 for 6 months, 1-year, 2-year, 3-year, 4-year and 5-year horizons are 17.1%, 28.7%, 41.3%, 36.2%, 34.8% and 34.9% respectively. Overall, we can see that the PC variable is a significant predictor of stock market returns.

Table XIV is presenting the results which can help us to compare different variables in the study in terms of both their power for predicting the returns (adjusted R^2) and statistical significance of the variables. The first two columns of the table are showing the results for short-horizon cases and the last two columns are presenting the results for the case of long-horizon predictions. In the 1-month horizon, PC is statistically significant and is showing 2.4% of adjusted R^2. The only other significant variables for this horizon are logGP and VRP. The adjusted R^2 of the two variables are respectively equal to 1.4% and 4%. The rest of the variables are not showing any statistical significance at this horizon. We can verify that the only variable which is providing higher adjusted R^2 than our PC variable is variance risk premium which is historically known as a strong variable for predicting stock market returns in the short horizons. The next horizon to look at is the 3-month horizon. In this case, the only significant variables are PC, logGP, and VRP. The adjusted R^2 of these three predictors in their univariate regressions are respectively 7.1%, 3.9%, and 7.8%. The adjusted R^2 for PC is still the second largest adjusted R^2 among all in this table. This shows that there are only a few variables known in the literature which are able to predict the returns in short horizon. Among those, PC which is introduced for the first time in this paper, is among one of the most significant and powerful predictors of stock market returns. The last two columns of the table are showing the results for the case of long-horizon predictability. Looking at the results in column three we can see that there are multiple significant variables in the 1-year horizon. PC variable still seems to be a variable with statistical significance and it is providing an adjusted R^2 of 28.7%. PC is showing the highest amount of the adjusted R^2 among all the predictors in this horizon. The variable is still a significant and powerful predictor of stock returns in the 5-year horizon and shows the highest adjusted R^2 among all the variables. In sum, it is evident that PC shows a high power for predicting stock market returns both in short and long horizons.

J. Stock Return Predictability-Bivariate

The question we want to ask in this section in the following: How does PC index works as a predictor of returns in comparison to other predictors, in a horse race? To answer this question we initially need to modify our regression model. The new model will look like:

$$\frac{12}{h}\sum_{i=1}^{h}\log R_{t+i} - \log R^f_{t+i} = \beta_0 + \beta_1 PC_t + \beta_2 X_t + \varepsilon_{t+h} \tag{15}$$

where X is the rival predictor that we want to investigate the effect of its presence. Table XV is presenting the results of all the bivariate regression for short horizons of 1 month and 3 months. The results for the short horizon analysis shows that not only the PC variables is a significant predictor in presence of all other variables in the analysis, but also the inclusion of this variable is going to make the other rival variables, except one, insignificant. The only variable which is keeping its significance across the regressions is the VRP. Even in the presence of VRP, the prediction power of PC is intact. Likewise, PC variable is showing statistical significance in all the regressions we run for the 3-month horizon. Also, the presence of this variable will make all other variables, except VRP, insignificant at this horizon.

Table XV is presenting the results for the case of long (1-year and 5-year) horizons. At the 1-year horizon, among all the variables that we have included in this horse race, none of them can reduce the significance level of our PC variable. Also, only CAY and VRP are the only variables which survive the inclusion of PC in the predictive regression. This is therefore an indication of the power of our variable in terms of predicting stock market returns in the long horizon, exactly like the case of the short horizon. The last case we want to take a look at within the framework of bivariate prediction power is the case of 5-year horizon. The second column of this table is presenting the results for this specific case. As we can see, PC is still a fully-significant predictor of stock returns across different regressions and after inclusion of different variables. Although three of rival predictors, logPD, logPE and TMSP, are statistically significant at this horizon, they are not having any effect on the significance of our variable. The sign of the coefficients related to PC are also stable and positive across different specifications.

All in all, we can conclude that our PC variable is a robust, significant and powerful predictor of stock market returns, both in the short and long horizons.

K. Out of Sample Prediction

Table XVII shows the results from the analysis related to the out-of-sample performance of PC using the data from 1990 to 2020. There are some differences between this table and the one which was presenting the out-of-sample performance of the GRNJ. First of all, we can see that the adjusted R^2 statistics are considerable and statistically significant across different horizons. Also, we can see that the magnitude of the out-of-sample adjusted R^2 is generally increasing going from 1-month towards 5-year horizons, both in the case of 120-month and 180-month, both in expanding and rolling setups. Because we do have a bigger sample size in this case, we can see that in contrast with the case of GRNJ in this case the adjusted R^2 is also increasing in the case of 180-month training window. All in all, we can see that PC is a significant and powerful predictor of stock market returns out-of-sample.

L. Determinants of PC

Table XVIII presents the results for the macroeconomic and uncertainty determinants of the PC variable. The results show that the only variable which is statistically significant at the 95% level is the DFSP. The default spread variable is the variable which measures the amount of distress in financial sector and the whole macroeconomy. In contrast with the previous case that the NVIX and its constituents were the most important determinants of GRNJ, in the case of PC only DFSP is statistically significant. Also, the contemporaneous regression of PC on DFSP is producing a high adjusted R^2 of 21.1% which shows that DFSP is a strong determinant of PC. Lastly, the positive sign of the coefficient on the DFSP shows that the higher is the DFSP the higher will be the value of PC variable which is in-line with the priors we had. This is a convincing signal that the PC variable can be interpreted as an index of financial distress and macroeconomic disaster, like it was the case for GRNJ.

M. Predicting Macro and Financial Variables

In this section, our goal is to investigate if the lags of PC variable are able to predict the most well-known macroeconomic variables and financial fear indices in the literature. Table XIX show the result of our attempt to investigate the prediction power of the variable using the first four lags of it. The first factor to look at is the NVIX factor. The results show that the coefficient associated with the first lag of the PC is statistically significant and its sign is also positive. It means that a higher value for the PC factor translates into having a higher overall fear perception in the financial markets and the economy. Also, we can see that the adjusted R^2 of the regression is 29% which is an indicator of the high power of the lags of PC for predicting NVIX.

The second variable under investigation in this section is the securities markets component of the NVIX. What we got as a result of running the regressions in this case can verify the fact that the predictability of NVIX can, to some extent, be tied to predictability of the securities markets component. The first lag of PC index is statistically significant at the 90% level and also positive, meaning that an increase in the PC will cause an increase in the securities markets component of the NVIX. The adjusted R^2 provided by the model is equal to 4.7%. The results show that there is a big part of predictability of the NVIX which cannot be explained away by the predictability of securities market component of NVIX.

The third column of the table is dedicated to the regression of PUI on the lags of PC. Our anticipation is that a higher PC will be translated into a higher policy uncertainty index in the United States' economy. The results show exactly the same thing. The first lag of the PC is statistically significant with positive sign. This means that an increase in the level of PC will cause an increase in the overall level of policy uncertainty index in the United States. The regression also produces a considerable adjusted R^2 of 11.8%, which shows that the link between PC and policy uncertainty index is pretty strong.

Column four shows the results for the case that we are trying to predict the intermediation component of NVIX. The results show that the first lag of the PC is positive in sign and statistically significant. Also the adjusted R^2 of the multi-variate predictive regression in this case is 6.81% which is greater in comparison to the case of the securities market part of the NVIX, which we looked at before. All in all, we can see that the lagged model we are using to predict intermediation component is considerably powerful model of prediction.

The results for the default spread are presented in the column five of the table. We expect the default spread to be an increasing function of PC. The results show that the coefficients on the first two lags of PC are positive and statistically significant. This is in-line with all the expectations we had before running the regressions. Also the adjusted R^2 generated by the regression of DFSP on the lags of PC is 14.4% which is showing the strong prediction power of the lags of PC for the DFSP variable. This is another sign that the PC variable is a successful proxy for the risk of macroeconomic disaster.

N. PC and Tail Risk

The suitable regression for investigating if the PC variable is related to tail risk in the market is:

$$\underbrace{SLOPE_t^{\Delta}}_{\sigma_{t,IV}^{OTM,\Delta}-\sigma_{t,IV}^{ATM}} = \beta_0 + \beta_1 PC_t + \beta_2 \sigma_{t,IV}^{ATM} + \varepsilon_t \tag{16}$$

Table XX presents the results for this case. As we can see, the PC is an statistically significant variable at the 95% level for all the levels of moneyness and the adjusted R^2 of the regressions are increasing when we go towards the slopes calculated based on the deeper OTM put options. Also, we can see that the inclusion of the implied volatility of the ATM option does not have any effect on the significance of the index in the regression. This is an indicator that PC variable is a measure of tail risk in the macroeconomy of the United States.

O. Predicting International Returns

Gold and other precious metals are globally traded assets, which is an indication that PC should be able to predict future stock returns in international markets. Here, we look at four different developed markets and see if PC is able to predict the stock returns in these countries. These four countries are UK, Switzerland, Japan and Sweden. We use the MSCI country indices for each of the four countries, which is denominated in the local currency of the country under investigation. The risk-free rate that we use in this analysis is the treasury bill rate for each of the countries. Table XXI is presenting the results for this analysis. The results are significant and the adjusted R^2 of the model is considerable for all the countries, in all the horizons. It is true that the results for the case of Sweden is weaker than the other three countries but even in this case the adjusted R^2 is considerable like the cases of the other three countries. The results suggest that PC can predict stock market returns in international markets and U.S. market both.

IV. Conclusion

The risk-return tradeoff is one of the main building blocks of pricing of financial assets. However, we have always seen the gap in the literature to identify a measure for risk which can robustly predict stock market returns in the time series, be a priced factor in the cross-section of stock returns and for which we are able to come up with a convincing economic intuition. In this paper we show that using the prices of short-term options on gold futures, we are able to derive an index which is related to aggregate source of risk in the economy. The index we have derived with the help of gold option prices can predict future stock returns in the time series, keeps its significance in presence of other well-known predictors in the literature and the index is priced in the cross-section of stock returns. Also, we can see that the measure can be tied to tail risk measures we derive based on the market options and also to the macroeconomic disaster measures available in the literature. The index also has the power to predict major macroeconomic and fear indices. In the latter part of the paper we augment our measure using prices of precious metals. We show that the new measure has all the properties of the option-based index in longer sample periods, having strong performance in predicting the returns in-sample and out-of-sample.

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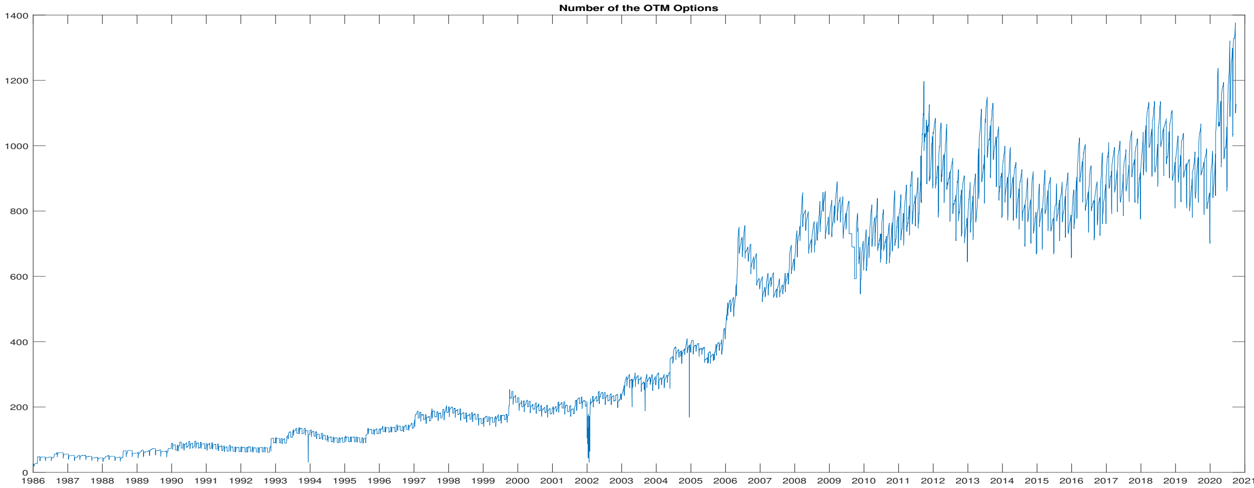
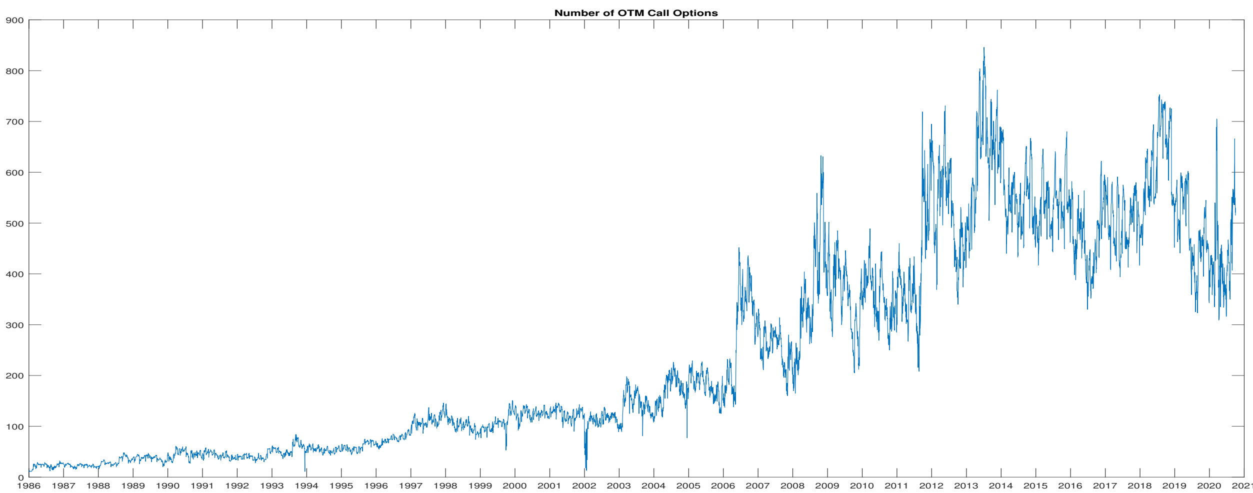
Figure 1.
Number of Out-of-the-Money Options in Gold Market



This panel shows the number of out-of-the-money options (put and call) in gold market from 1986-2020. The number shows the aggregate number of options across different strike prices at each day. The open interest and the volume of the options are not taken into account.

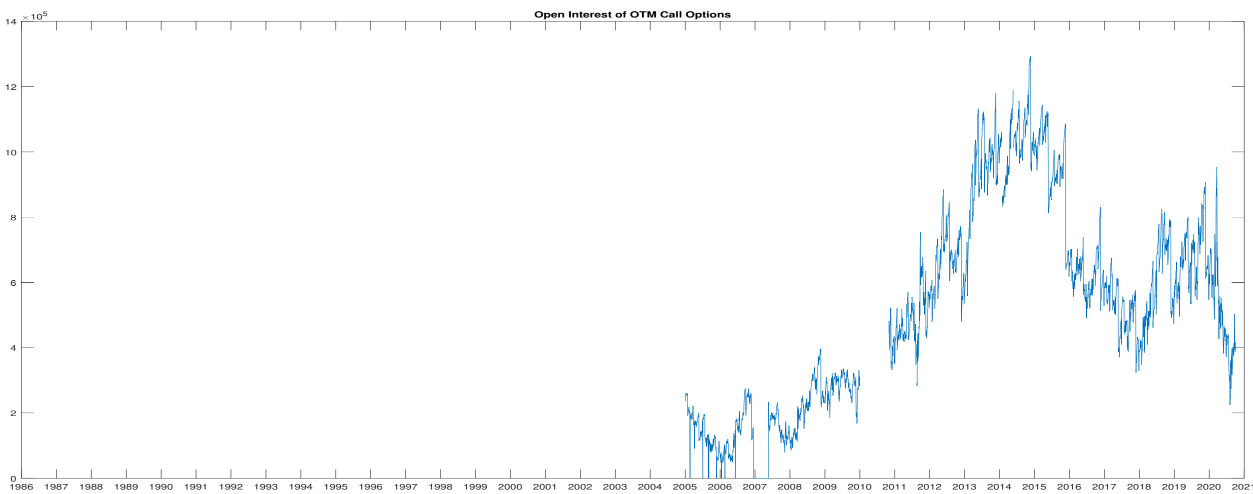
Figure 2.
Number of Out-of-the-Money Call Options in Gold Market



This panel shows the number of out-of-the-money call options in gold market from 1986-2020. The number shows the aggregate number of options across different strike prices at each day. The open interest and the volume of the options are not taken into account.

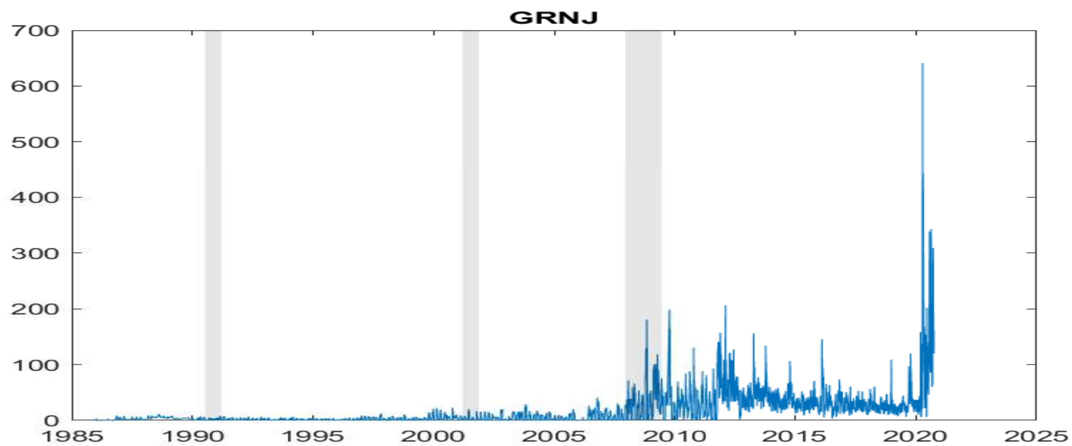
Figure 3.

Open Interest of Out-of-the Money Call Options in Gold Market



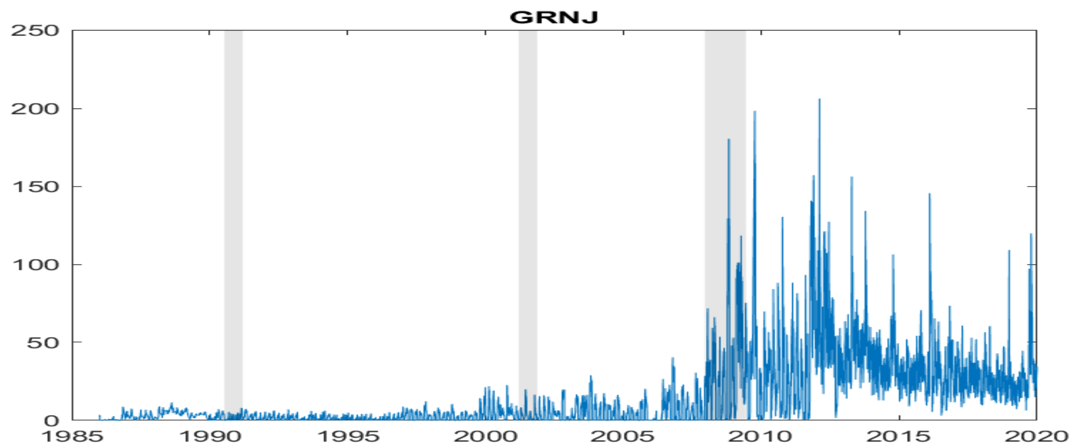
This panel shows the total open interest of out-of-the-money call options in gold market from 1986-2020. The number shows the aggregate open interest of options across different strike prices at each day.

Figure 4.
Gold Risk-Neutral Jump Including Covid-19



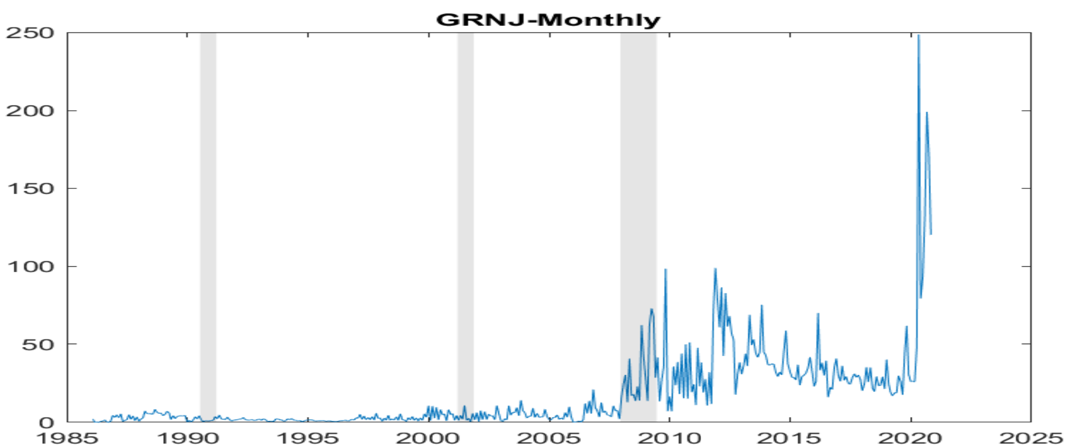
This panel shows the daily time series of Gold Risk-Neutral Jump from 1986-2020. The panel includes the period of Covid-19 crisis.

Figure 5.
Gold Risk-Neutral Jump Excluding Covid-19



This panel shows the daily time series of Gold Risk-Neutral Jump from 1986-2020. The panel does not include the period of Covid-19 crisis.

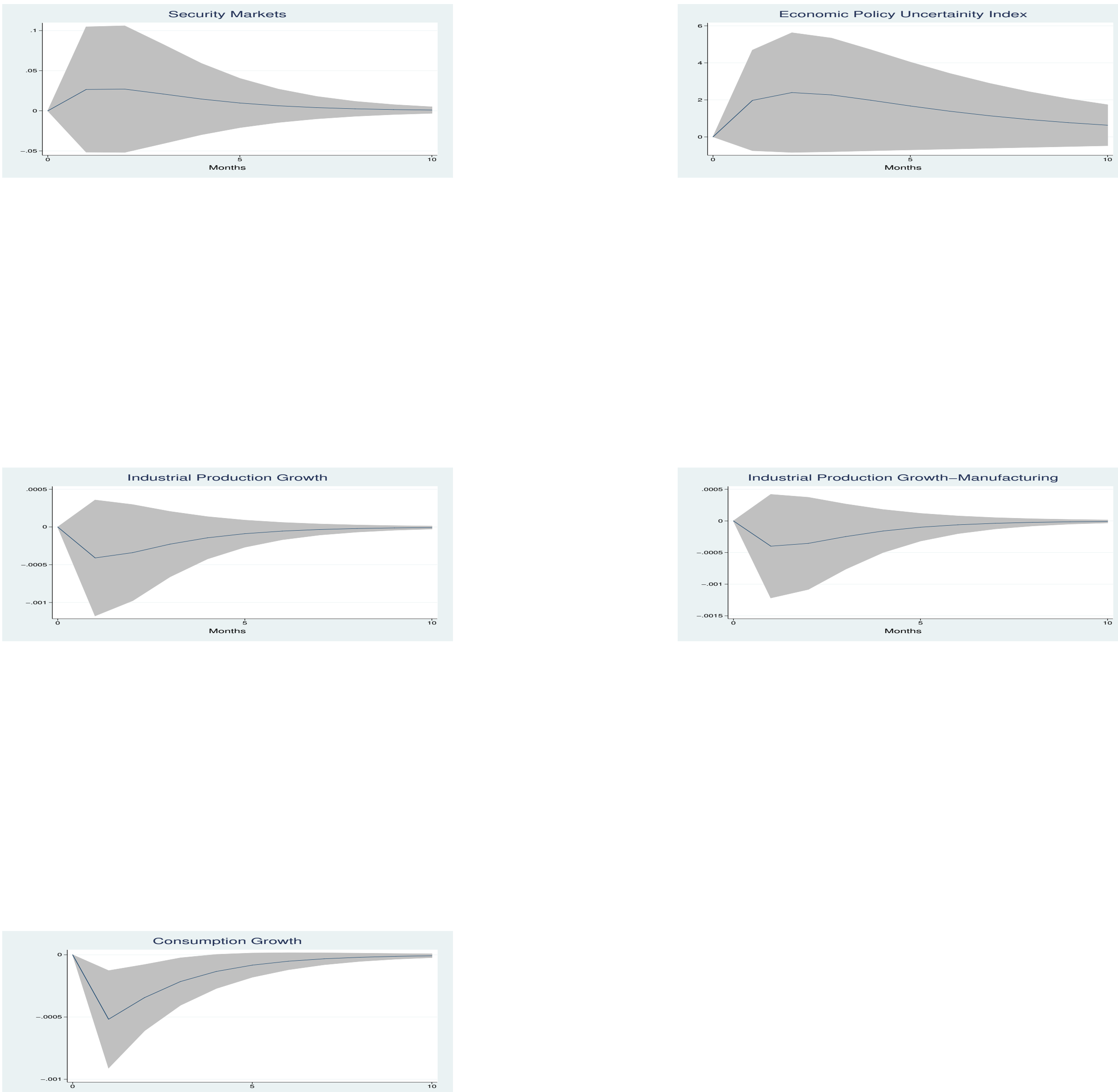
Figure 6.
Gold Risk-Neutral Jump-Monthly Frequency



This panel shows the monthly time series of Gold Risk-Neutral Jump from 1986-2020. The panel includes the period of Covid-19 crisis.

Figure 7.

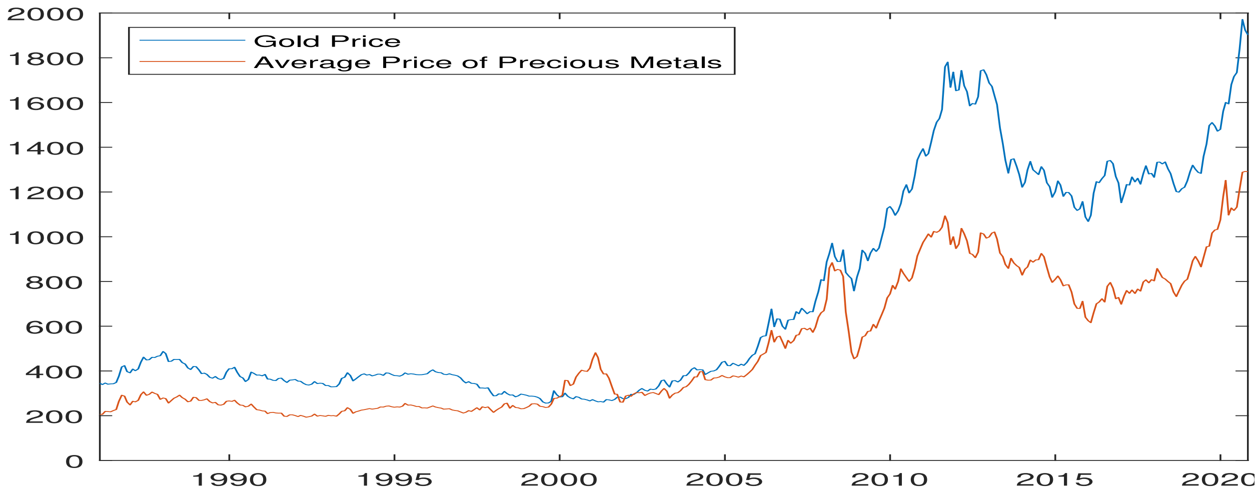
Impulse Response Functions



This figure shows the cumulative impulse response of Security Markets, Economic Policy Uncertainty Index, Industrial Production Growth, Industrial Production Growth-Manufacturing and Consumption Growth.

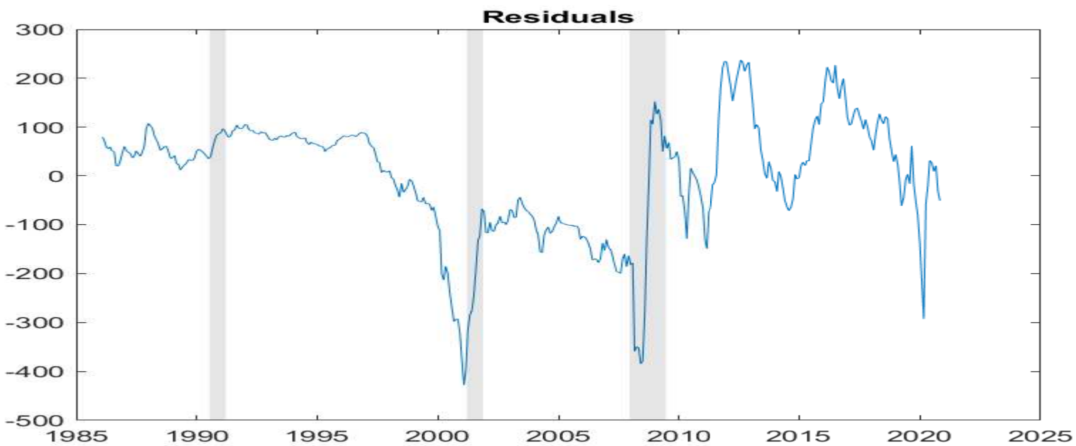
Figure 8.

Gold Price and Average Price of Precious Metals 1986-2020.



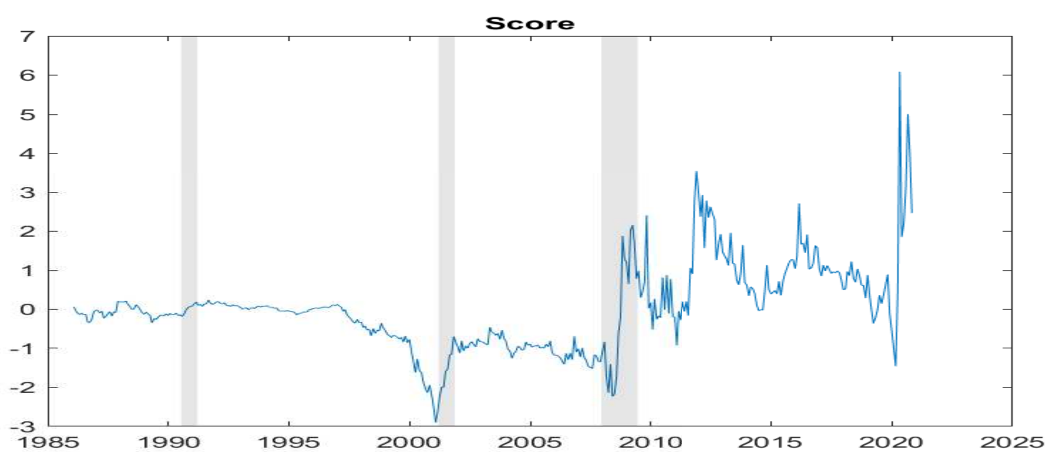
This panel shows the monthly price of gold (blue line) and the average price of precious metals (orange line) from 1986-2020.

Figure 9.
Residuals of the Regression of Gold Price on Average Price of Precious Metals



This panel shows the residuals of the regression of gold price on average price of precious metals, including gold, from 1986-2020. The shaded grey bars are NBER recessions.

Figure 10.
Scores of the First Principal Component of Residuals and GRNJ



This panel shows the scores from the first principal component of the residuals and GRNJ from 1986-2020. The shaded grey bars are NBER recessions.

Table I: Summary Statistics for Predictors

Table I gives descriptive statistics for GRNJ and other known stock returns predictors. Monthly data from 2004-2019. $GRNJ_t$ is the monthly average of the risk-neutral jump index in the gold market. $\log PE_t$ is cyclically-adjusted price to earning ratio from Robert Shiller's website. $\log GP_t$ is the log of the ratio of monthly gold to platinum fixing prices. Gold fixing price are from the LBMA, the platinum fixing price is from LPPM. $\log PD_t$ is the log price-dividend ratio for the CRSP value-weighted index. $\log PNY_t$ is the net payout yield from Michael Robert's website, available until December 2010. CAY_t is the consumption-welath ratio from Lettau and Ludvigson (2001) and the data is from Martin Lettau's website, available until March 2013. VRP_t is the variance risk premium, calculated as the difference between risk-neutral and physical variance. The data is from Hao Zhou's website. $DFSP_t$ is default spread which is the difference between the yield of Aaa and Baa corporate bonds; the data is from FRED. $Inflation_t$ is the growth rate of the consumer price index from FRED. $TMSP_t$ is the term spread, calculated as the difference between a 10 year constant maturity U.S. government bond and a 3 month constant maturity U.S. treasury bill. The data is taken from FRED. ADF is the augmented Dickey and Fuller (1979) test statistic, and p-val is its p-value.

	Mean	Std. dev.	AR(1)	ADF	p-val	Min	Max	Corr.GRNJ
$GRNJ_t$	17.222	19.214	-0.702	-3.796	0.001	0.111	98.340	1.000
$\log PE_t$	3.140	0.187	-1.000	-0.413	0.498	2.589	3.320	-0.677
$\log GP_t$	-0.525	0.226	-0.995	-1.217	0.204	-0.842	-0.034	0.642
$\log PD_t$	3.932	0.193	-1.000	-0.415	0.497	3.324	4.164	-0.663
$\log PNY_t$	2.261	0.112	-1.000	-0.112	0.608	2.046	2.496	-0.268
CAY_t	0.000	0.007	-0.938	-1.289	0.181	-0.016	0.018	-0.115
VRP_t	0.118	0.296	-0.287	-6.871	0.001	-2.186	0.778	0.071
$DFSP_t$	1.179	0.614	-0.992	-0.600	0.429	0.620	3.380	0.593
$Inflation_t$	0.002	0.004	-0.586	-4.681	0.001	-0.018	0.014	-0.243
$TMSP_t$	1.841	1.372	-0.993	-0.498	0.467	-0.515	3.685	0.449

Table II: U.S. stock return predictability

This table shows return predictability for the U.S. equity market, January 2004 to December 2019, 192 monthly observations. The regression equation is:

$$\frac{12}{h}\sum_{i=1}^{h}\log R_{t+i} - \log R^f_{t+i} = \beta_0 + \beta_1 GRNJ_{\rm t} + \varepsilon_{t+h}$$

The left hand side variable is the excess return on the CRSP value-weighted index, annualized by horizon h. The right hand side predictor is $GRNJ_{\rm t}$. The returns are calculated based on overlapping monthly data, and standard errors are based on Newey and West (1987) HAC robust standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1m	3m	6m	1y	2y	3y	4y	5y
$GRNJ_t$	0.00521**	0.00330***	0.00302**	0.00268**	0.00272***	0.00256**	0.00244***	0.00223***
	(0.00202)	(0.000943)	(0.00116)	(0.00104)	(0.000779)	(0.000847)	(0.000519)	(0.000448)
_cons	-0.0727	-0.0201	-0.0120	-0.00338	-0.00686	-0.00575	-0.00595	-0.0000490
	(0.0801)	(0.0559)	(0.0604)	(0.0577)	(0.0370)	(0.0415)	(0.0238)	(0.0228)
R^2_{adj}	0.045	0.049	0.071	0.113	0.220	0.313	0.382	0.416

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table III. Univariate Return Predictability-Rival Predictors

This table shows return predictability for the U.S. equity market using rival return predictors, January 2004 to December 2019, 192 monthly observations. The regression is:

$$\frac{12}{h}\sum_{i=1}^{h}\log R_{t+i} - \log R^f_{t+i} = \beta_0 + \beta_1 X_t + \varepsilon_{t+h}$$

The left had side variable is the excess return on the CRSP value-weighted index, annualized by horizon h. The right hand side predictor is X_t, which are the rival predictors. The returns are calculated based on overlapping monthly data, and standard errors are based on Newey and West (1987) HAC robust standard errors.

	1m			3m			1y			5y		
	Coef	tstat	R^2_{adj}	Coef	tstat	R^2_{adj}	Coef	tstat	R^2_{adj}	Coef	tstat	R^2_{adj}
$GRNJ_t$	0.005	3.219	0.045	0.003	3.651	0.049	0.003	2.932	0.113	0.002	6.642	0.416
$\log GP_t$	0.145	2.090	0.010	0.163	1.932	0.045	0.171	1.889	0.180	0.074	1.276	0.172
$\log PD_t$	−0.190	−0.402	−0.002	−0.235	−0.688	0.007	−0.358	−4.699	0.090	−0.346	−5.517	0.454
$\log PE_t$	−0.276	−1.127	0.005	−0.314	−2.056	0.029	−0.272	−2.147	0.080	−0.283	−5.500	0.470
$\log PNY_t$	0.956	1.086	0.028	0.930	1.078	0.072	0.468	1.445	0.052	−0.106	−0.754	0.009
CAY_t	−13.449	−1.996	0.029	−9.026	−1.647	0.031	−4.336	−1.127	0.020	−4.475	−2.148	0.154
VRP_t	0.623	3.930	0.076	0.430	4.903	0.098	0.093	1.437	0.011	0.065	1.234	0.035
$DFSP_t$	−0.080	−0.525	0.001	−0.026	−0.279	−0.003	0.056	2.372	0.021	0.066	3.859	0.186
$Inflation_t$	3.267	0.262	−0.005	7.398	0.509	0.001	−13.869	−2.180	0.065	−5.367	−3.721	0.050
$TMSP_t$	−0.011	−0.384	−0.005	−0.010	−0.501	−0.004	0.029	1.856	0.037	0.041	4.493	0.418

Table IV: Bivariate Return Predictability: Short Horizon

This table shows return predictability for the U.S. equity market for 1 and 3 month horizons, controlling for other known predictors. January 2004 to December 2019, 192 monthly observations. The regression is:

$$\frac{12}{h}\sum_{i=1}^{h}\log R_{t+i} - \log R^f_{t+i} = \beta_0 + \beta_1 GRNJ_t + \beta_2 X_t + \varepsilon_{t+h}$$

The left had side variable is the excess return on the CRSP value-weighted index, annualized by horizon h (here, h=1 and h=3). The right hand side predictors are $GRNJ_t$ and another return predictor X_t, which is picked from the rival predictors. The returns are calculated based on overlapping monthly data, and standard errors are based on Newey and West (1987) HAC robust standard errors.

	1m					3m				
	$GRNJ_t$	tstat	Coef	tstat	R^2_{adj}	$GRNJ_t$	tstat	Coef	tstat	R^2_{adj}
$\log GP_t$	0.005	2.375	0.014	0.155	0.040	0.003	1.999	0.068	0.736	0.047
$\log PD_t$	0.006	2.292	0.248	0.412	0.044	0.003	1.884	−0.031	−0.061	0.041
$\log PE_t$	0.006	2.802	0.103	0.281	0.041	0.003	2.632	−0.067	−0.219	0.042
CAY_t	0.005	2.761	−4.765	−1.293	0.055	0.003	2.540	−4.461	−1.305	0.083
VRP_t	0.005	3.206	0.618	4.520	0.120	0.003	3.272	0.422	6.442	0.136
$DFSP_t$	0.006	3.256	−16.056	−1.097	0.063	0.004	3.391	−6.767	−0.504	0.051
$Inflation_t$	0.006	3.284	25.886	1.297	0.067	0.004	3.335	16.789	1.070	0.070
$TMSP_t$	0.006	3.219	−3.986	−1.253	0.048	0.004	3.361	−2.010	−0.720	0.046

Table V: Bivariate Return Predictability: Long Horizon

This table shows return predictability for the U.S. equity market for 1 and 5 year horizons, controlling for other known predictors. January 2004 to December 2019, 192 monthly observations. The regression is:

$$\frac{12}{h}\sum_{i=1}^{h}\log R_{t+i} - \log R^f_{t+i} = \beta_0 + \beta_1 GRNJ_t + \beta_2 X_t + \varepsilon_{t+h}$$

The left had side variable is the excess return on the CRSP value-weighted index, annualized by horizon h (here, h=12 and h=60). The right hand side predictors are $GRNJ_t$ and another return predictor X_t, which is picked from the rival predictors. The returns are calculated based on overlapping monthly data, and standard errors are based on Newey and West (1987) HAC robust standard errors.

	1y					5y				
	$GRNJ_t$	tstat	Coef	tstat	R^2_{adj}	$GRNJ_t$	tstat	Coef	tstat	R^2_{adj}
$\log GP_t$	0.001	1.836	0.132	1.801	0.198	0.002	5.868	0.055	2.795	0.511
$\log PD_t$	0.002	2.541	−0.209	−1.626	0.138	0.001	5.636	−0.247	−4.796	0.613
$\log PE_t$	0.002	2.992	−0.149	−1.686	0.137	0.002	4.854	−0.150	−5.033	0.555
CAY_t	0.003	3.854	−1.722	−1.000	0.136	0.002	7.605	−0.995	−2.110	0.494
VRP_t	0.003	3.679	0.084	1.930	0.127	0.002	6.445	0.048	1.833	0.457
$DFSP_t$	0.003	3.277	2.244	0.494	0.118	0.002	5.868	3.706	5.142	0.491
$Inflation_t$	0.002	3.698	−8.610	−1.331	0.140	0.002	6.324	−2.268	−1.641	0.444
$TMSP_t$	0.003	3.874	1.679	1.305	0.127	0.002	4.949	2.649	4.060	0.602

Table VI: Out of Sample Prediction

This table shows results for out-of-sample testing, using the out-of-sample adjusted R^2 statistic. Let T be the sample length, and m equal to the size of initial training window (for expanding regressions) or the size of the training window (for rolling regressions). The Out-of-Sample adjusted R^2 is given by:

$$R^2_{OS} = 1 - \frac{\sum_{k=1}^{T-m} (r^e_{m+k} - \hat{r}^e_{m+k})^2}{\sum_{k=1}^{T-m} (r^e_{m+k} - \bar{r}^e_{m+k})^2}$$

For expanding window regressions, the first out-of-sample forecast $\hat{r}^e_{m+1}$ is based on parameters estimated using observations from 1 to m, the second out-of-sample forecast $\hat{r}^e_{m+2}$ is based on parameters estimated using observations 1 to m+1, and so on. For expanding window regressions, the historical average excess return $\bar{r}^e_{m+1}$ is calculated as the average excess return from time 1 to t. For rolling window regressions, the first out-of-sample forecast $\hat{r}^e_{m+1}$ is based on parameters estimated using observations from 1 to m, the second out-of-sample forecast $\hat{r}^e_{m+2}$ is based on parameters estimated using observations 2 to m+1, and so on. For rolling window regressions, the historical average excess return is calculated as the average excess return from over the last m periods, where m is the window length. We consider windows of length 120 months or 180 months to estimate betas, and predict the return in the next month. The p-values are calculated using the adjusted-MSPE statistic of Clark and West (2007) given by:

$$f_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - [(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2]$$

Which is regressed against a constant and the test is a one-sided test.

	$120m_{\text{exp}}$	pval	$180m_{\text{exp}}$	pval	$120m_{roll}$	pval	$180m_{roll}$	pval
1m	0.070	0.002	0.076	0.013	0.041	0.020	0.059	0.026
3m	0.173	0.000	0.125	0.003	0.085	0.002	0.076	0.012
6m	0.291	0.000	0.188	0.001	0.151	0.000	0.083	0.011
1y	0.453	0.000	0.260	0.000	0.274	0.000	0.128	0.004
2y	0.562	0.000	0.333	0.000	0.393	0.000	0.239	0.000
3y	0.527	0.000	0.267	0.000	0.386	0.000	0.214	0.000
4y	0.460	0.000	0.117	0.002	0.344	0.000	0.148	0.000
5y	0.443	0.000	-0.085	0.008	0.345	0.000	0.072	0.000

Table VII: Cross-Sectional Implications

At the end of each month, we run regression (11) on daily returns in that month. We sort the stocks into 5 quintiles based on $GRNJ$ regression coefficient, β_{GRNJ}, the first quintile having lowest and the fifth quintile having highest exposure. Then we form a value-weighted portfolio for each quintile, each stock having weight equal to its value divided by the aggregate value of the stocks in that portfolio. Then we get the post-ranking daily returns of each of these five portfolios for the month following the portfolio-formation period. We roll the beta estimation period one month and keep doing the same procedure until we cover the whole sample. At the end of this procedure, we have the daily returns of these five portfolios and monthly pre-ranking β_{GRNJ} for all portfolios. This table reports the average pre-ranking beta and average monthly return for each of the five portfolios. We also compute Jensen's Alpha of the Carhart 4-Factor model by regressing daily returns on SMB, HML, UMD and Rm-Rf (regression 12). The reported alphas are computed by multiplying daily alpha by 21. The reported numbers are in percent. We also report the p-value of Carhart alpha. The results are presented in the following table.

	1	2	3	4	5	5-1
Average Beta	-0.005	-0.001	0.000	0.002	0.006	0.011
Average Returns	0.855	0.825	0.695	0.648	0.487	-0.368
Average Jensen's Alpha	0.071	0.143	0.045	-0.016	-0.284	-0.356
P-Value	0.673	0.098	0.396	0.867	0.184	0.254

Table VIII: Constituents of NVIX as Determinants of GRNJ

This table shows the results for determinants of GRNJ using the constituents of NVIX regression, January 2004 to December 2019, 192 monthly observations. The regression is:

$$GRNJ_t = \beta_0 + \beta_1 X_t + \varepsilon_{t+h}$$

The left had side variable is the GRNJ and the right hand side variable, X, is one of the constituents of NVIX. The standard errors are based on Newey and West (1987) HAC robust standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$GRNJ_t$	$GRNJ_t$	$GRNJ_t$	$GRNJ_t$	$GRNJ_t$	$GRNJ_t$	$GRNJ_t$
$Intermediation_t$	7.828*						
	(3.535)						
$SecuritiesMarkets_t$		11.02*					
		(4.330)					
$Government_t$			34.27***				
			(8.714)				
War_t				-60.89*			
				(26.25)			
$Unclassified_t$					2.082***		
					(0.455)		
$NaturalDisaster_t$						-179.4	
						(144.0)	
$NVIX_t$							1.654***
							(0.405)
Constant	16.03*	8.685	3.368	28.52***	7.836	23.10**	-14.89
	(8.084)	(11.04)	(8.299)	(6.034)	(4.013)	(7.461)	(9.827)
R^2_{adj}	0.128	0.109	0.223	0.050	0.350	0.009	0.321

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table IX: Macroeconomic Determinants of GRNJ

This table shows regression results to identify the determinants of $GRNJ$, January 2004 to December 2019, 192 monthly observations. The regression is:

$$GRNJ_t = \beta_0 + \beta_1 X_t + \varepsilon_t$$

The left hand side variable is $GRNJ_t$. The right hand side predictor , X_t, is one of eight macroeconomic and fear indices which are shown in the first column of the table.

	$GRNJ_t$
$NVIX_t$	1.911***
	(0.530)
$NVIX_{SM_t}$	-2.645
	(3.402)
PUI_t	0.00926
	(0.0675)
$TedSpread_t$	-7.495
	(4.110)
ΔIP_t	-312.7
	(309.2)
$DFSP_t$	16.88
	(11.19)
$\Delta IPMAN$	-310.7
	(466.7)
ΔPCE	-214.8
	(332.1)
Constant	-26.67**
	(9.438)
R^2_{adj}	0.396

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table X: Predicting macroeconomic and fear variables by the lags of $GRNJ$

This table shows predictability regressions for macroeconomic variables, January 2004 to December 2019, 192 monthly observations. The regression is:

$$X_t = \beta_0 + \sum_{i=1}^{4} \beta_i GRNJ_{t-i} + \varepsilon_t$$

The left had side variable is one of the five macroeconomic-fear variables at the top row of the table. The right hand side predictor are the first four lags of $GRNJ$.

	(1) $NVIX_t$	(2) $NVIX_{SM_t}$	(3) PUI_t	(4) $Intermediation_t$	(5) ΔIP_t
$GRNJ_{t-1}$	0.104**	0.00165	0.483***	0.00708*	-0.0000361
	(0.0360)	(0.00293)	(0.137)	(0.00325)	(0.0000309)
$GRNJ_{t-2}$	0.00816	0.000853	0.0925	0.00535*	-0.0000145
	(0.0170)	(0.00187)	(0.0853)	(0.00263)	(0.0000379)
$GRNJ_{t-3}$	0.0482*	0.00181	0.168	0.00362	-0.00000308
	(0.0198)	(0.00262)	(0.125)	(0.00408)	(0.0000311)
$GRNJ_{t-4}$	0.0720**	0.00554*	0.341**	0.000986	0.0000368
	(0.0274)	(0.00249)	(0.116)	(0.00414)	(0.0000364)
Constant	19.44***	1.456***	87.98***	1.022**	0.00125
	(2.701)	(0.218)	(10.66)	(0.374)	(0.000999)
R^2_{adj}	0.300	0.049	0.217	0.071	-0.007

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XI: Predicting macroeconomic and fear variables by the lags of $GRNJ$ II

This table shows predictability regressions for macroeconomic variables, January 2004 to December 2019, 192 monthly observations. The regression is:

$$X_t = \beta_0 + \sum_{i=1}^{4} \beta_i GRNJ_{t-i} + \varepsilon_t$$

The left had side variable is one of the five macroeconomic-fear variables at the top row of the table. The right hand side predictor are the first four lags of $GRNJ$.

	(1)	(2)	(3)	(4)	(5)
	VIX_t	ADS_t	$DFSP_t$	$\Delta IPMAN_t$	ΔPCE_t
$GRNJ_{t-1}$	0.0989*	-0.00273	0.00527*	-0.0000226	-0.0000523*
	(0.0404)	(0.00380)	(0.00262)	(0.0000345)	(0.0000213)
$GRNJ_{t-2}$	0.00859	-0.00208	0.00373*	-0.0000435	0.0000179
	(0.0203)	(0.00307)	(0.00156)	(0.0000524)	(0.0000162)
$GRNJ_{t-3}$	-0.0323	-0.000718	-0.000390	-0.0000140	0.0000159
	(0.0243)	(0.00185)	(0.00120)	(0.0000427)	(0.0000240)
$GRNJ_{t-4}$	-0.00540	0.00226	-0.00159	0.0000502	-0.0000129
	(0.0294)	(0.00339)	(0.00174)	(0.0000504)	(0.0000163)
Constant	16.27***	-0.205	0.862***	0.00143	0.00411***
	(2.191)	(0.179)	(0.0685)	(0.00129)	(0.000493)
R^2_{adj}	0.022	-0.011	0.075	-0.001	0.036

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XII: GRNJ and Tail Risk

In this table, $SLOPE_t^{n\Delta} = \sigma_t^{OTM,\Delta} - \sigma_t^{ATM}$, where $\sigma_t^{OTM,\Delta}$ is the implied volatility of on out-of-the-money put option with nΔ, where n=40, 30, 20, and σ_t^{ATM} is at-the-money implied volatility. Option prices and implied volatilities are from OptionMetrics, January 1996 to December 2019. The regression of the slope of the implied volatility curve for index options against the GRNJ index is:

$$\sigma_t^{OTM,\Delta} - \sigma_t^{ATM} = \beta_0 + \beta_1 GRNJ_t + \beta_2 \sigma_t^{ATM} + \varepsilon_t$$

The OTM options ranges from deep out-of-the-money (20Δ) to slightly out-of-the-money (40Δ), and the at-the-money option is defined as a put option with 50Δ. The options have just under one month until expiration, and are taken on the last trading day of the month.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Slope_t^{20\Delta}$	$Slope_t^{20\Delta}$	$Slope_t^{30\Delta}$	$Slope_t^{30\Delta}$	$Slope_t^{40\Delta}$	$Slope_t^{40\Delta}$
$GRNJ_t$	0.00181**	0.000614	0.00392**	0.00133*	0.00689**	0.00268*
	(0.000599)	(0.000322)	(0.00132)	(0.000663)	(0.00230)	(0.00105)
σ_{ATM_t}		0.0506***		0.109***		0.177***
		(0.00499)		(0.0107)		(0.0176)
_cons	0.170***	0.0300	0.393***	0.0921*	0.747***	0.257***
	(0.0239)	(0.0194)	(0.0519)	(0.0404)	(0.0890)	(0.0641)
R^2_{adj}	0.132	0.772	0.131	0.760	0.143	0.730

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XIII: U.S. Stock Return Predictability

This table shows return predictability for the U.S. equity market, January 1990 to December 2019, 360 monthly observations. The regression equation is:

$$\frac{12}{h}\sum_{i=1}^{h}\log R_{t+i} - \log R^f_{t+i} = \beta_0 + \beta_1 PC_t + \varepsilon_{t+h}$$

The left hand side variable is the excess return on the CRSP value-weighted index, annualized by horizon h. The right hand side predictor is PC_t . The returns are calculated based on overlapping monthly data, and standard errors are based on Newey and West (1987) HAC robust standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1m	3m	6m	1y	2y	3y	4y	5y
PC_t	0.0863***	0.0838***	0.0917***	0.0861***	0.0770***	0.0604***	0.0515***	0.0455***
	(0.0245)	(0.0175)	(0.0142)	(0.0105)	(0.00699)	(0.00515)	(0.00402)	(0.00338)
_cons	0.0752**	0.0729***	0.0720***	0.0710***	0.0675***	0.0659***	0.0633***	0.0614***
	(0.0256)	(0.0184)	(0.0127)	(0.00869)	(0.00592)	(0.00523)	(0.00467)	(0.00414)
R^2_{adj}	0.024	0.071	0.171	0.287	0.413	0.362	0.348	0.349

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XIV: Univariate Return Predictability-Rival Predictors

This table shows return predictability for the U.S. equity market using rival return predictors, January 1990 to December 2019, 360 monthly observations. The regression is:

$$\frac{12}{h}\sum_{i=1}^{h}\log R_{t+i} - \log R^f_{t+i} = \beta_0 + \beta_1 X_t + \varepsilon_{t+h}$$

The left hand side variable is the excess return on the CRSP value-weighted index, annualized by horizon h. The right hand side predictor is X_t, which is one of the rival predictors. The returns are calculated based on overlapping monthly data, and standard errors are based on Newey and West (1987) HAC robust standard errors.

	1m			3m			1y			5y		
	Coef	tstat	R^2_{adj}	Coef	tstat	R^2_{adj}	Coef	tstat	R^2_{adj}	Coef	tstat	R^2_{adj}
PC_t	0.086	3.507	0.024	0.085	4.477	0.071	0.086	3.673	0.287	0.050	6.746	0.415
$\log GP_t$	0.206	3.022	0.014	0.194	2.245	0.039	0.211	2.431	0.185	0.123	3.003	0.276
$\log PD_t$	−0.150	−1.611	0.005	−0.148	−1.918	0.019	−0.148	−1.860	0.079	−0.138	−2.253	0.305
$\log PE_t$	−0.135	−1.286	0.003	−0.133	−1.677	0.013	−0.137	−1.604	0.058	−0.142	−1.977	0.282
$\log PNY_t$	0.154	0.996	0.001	0.139	0.867	0.007	0.149	1.027	0.039	0.127	2.712	0.137
CAY_t	−1.422	−1.037	0.000	−0.940	−0.810	0.000	−0.138	−0.129	−0.002	−0.644	−1.048	0.020
VRP_t	0.511	4.541	0.040	0.419	6.904	0.078	0.091	1.649	0.010	−0.036	−0.869	0.006
$DFSP_t$	−5.794	−0.480	−0.001	−3.384	−0.426	−0.001	2.785	0.605	0.002	5.169	1.760	0.063
$Inflation_t$	−3.653	−0.356	−0.002	2.114	0.191	−0.002	−11.358	−2.565	0.031	−4.161	−3.265	0.017
$TMSP_t$	−1.322	−0.566	−0.002	−0.590	−0.283	−0.002	2.076	1.556	0.020	4.022	5.343	0.357

Table XV: Bivariate Return Predictability-Short Horizon

This table shows return predictability for the U.S. equity market for 1 and 3 month horizons, controlling for other known predictors. January 1990 to December 2019, 360 monthly observations. The regression is:

$$\frac{12}{h}\sum_{i=1}^{h} \log R_{t+i} - \log R^f_{t+i} = \beta_0 + \beta_1 PC_t + \beta_2 X_t + \varepsilon_{t+h}$$

The left hand side variable is the excess return on the CRSP value-weighted index, annualized by horizon h (here, h=1 and h=3). The right hand side predictors are PC_t and another rival return predictor X_t. The returns are calculated based on overlapping monthly data, and standard errors are based on Newey and West (1987) HAC robust standard errors.

	1m					3m				
	PC_t	tstat	Coef	tstat	R^2_{adj}	PC_t	tstat	Coef	tstat	R^2_{adj}
$\log GP_t$	0.084	2.083	0.011	0.094	0.022	0.088	2.691	−0.010	−0.096	0.069
$\log PD_t$	0.081	3.994	−0.048	−0.584	0.022	0.079	4.287	−0.048	−0.669	0.071
$\log PE_t$	0.082	4.125	−0.044	−0.495	0.022	0.081	4.389	−0.045	−0.581	0.070
$\log PNY_t$	0.141	3.329	−0.071	−0.563	0.024	0.142	3.932	−0.088	−0.686	0.079
CAY_t	0.089	3.732	0.450	0.352	0.021	0.090	4.442	0.956	0.853	0.070
VRP_t	0.100	4.909	0.578	5.965	0.081	0.097	5.162	0.484	8.837	0.191
$DFSP_t$	0.100	4.729	−12.934	−1.082	0.030	0.096	4.893	−10.225	−0.962	0.083
$Inflation_t$	0.089	4.080	4.326	0.352	0.022	0.091	4.586	10.307	0.851	0.076
$TMSP_t$	0.096	4.323	−3.332	−1.488	0.026	0.092	4.606	−2.525	−1.229	0.077

Table XVI: Bivariate Return Predictability-Long Horizon

This table shows return predictability for the U.S. equity market for 1 and 5 year horizons, controlling for other known predictors. January 1990 to December 2019, 360 monthly observations. The regression is:

$$\frac{12}{h}\sum_{i=1}^{h} \log R_{t+i} - \log R^f_{t+i} = \beta_0 + \beta_1 PC_t + \beta_2 X_t + \varepsilon_{t+h}$$

The left had side variable is the excess return on the CRSP value-weighted index, annualized by horizon h (here, h=12 and h=60). The right hand side predictors are PC_t and another return predictor X_t. The returns are calculated based on overlapping monthly data, and standard errors are based on Newey and West (1987) HAC robust standard errors.

	1y					5y				
	PC_t	tstat	Coef	tstat	R^2_{adj}	PC_t	tstat	Coef	tstat	R^2_{adj}
$\log GP_t$	0.081	4.416	0.022	0.402	0.286	0.045	5.069	0.018	0.619	0.415
$\log PD_t$	0.081	4.798	−0.047	−1.075	0.292	0.039	9.006	−0.089	−3.948	0.522
$\log PE_t$	0.082	4.874	−0.047	−1.031	0.292	0.041	8.897	−0.098	−4.608	0.534
$\log PNY_t$	0.151	4.803	−0.092	−0.978	0.349	0.070	6.366	0.015	0.398	0.440
CAY_t	0.100	5.328	1.977	2.893	0.329	0.053	8.234	0.480	1.293	0.428
VRP_t	0.090	5.250	0.151	2.999	0.351	0.049	9.048	−0.003	−0.140	0.418
$DFSP_t$	0.090	5.015	−3.665	−0.798	0.293	0.048	8.742	1.747	1.243	0.420
$Inflation_t$	0.084	5.115	−3.803	−1.232	0.289	0.050	9.033	0.323	0.298	0.413
$TMSP_t$	0.086	5.031	0.275	0.242	0.286	0.041	8.560	3.161	6.457	0.623

Table XVII: Out of Sample Prediction

This table shows results for out-of-sample testing, using the out-of-sample adjusted R^2 statistic. Let T be the sample length, and m equal to the size of initial training window (for expanding regressions) or the size of the training window (for rolling regressions). The Out-of-Sample adjusted R^2 is given by:

$$R^2_{OS} = 1 - \frac{\sum_{k=1}^{T-m} (r^e_{m+k} - \hat{r}^e_{m+k})^2}{\sum_{k=1}^{T-m} (r^e_{m+k} - \bar{r}^e_{m+k})^2}$$

For expanding window regressions, the first out-of-sample forecast $\hat{r}^e_{m+1}$ is based on parameters estimated using observations from 1 to m, the second out-of-sample forecast $\hat{r}^e_{m+2}$ is based on parameters estimated using observations 1 to m+1, and so on. For expanding window regressions, the historical average excess return $\bar{r}^e_{m+1}$ is calculated as the average excess return from time 1 to t. For rolling window regressions, the first out-of-sample forecast $\hat{r}^e_{m+1}$ is based on parameters estimated using observations from 1 to m, the second out-of-sample forecast $\hat{r}^e_{m+2}$ is based on parameters estimated using observations 2 to m+1, and so on. For rolling window regressions, the historical average excess return is calculated as the average excess return from over the last m periods, where m is the window length. We consider windows of length 120 months or 180 months to estimate betas, and predict the return in the next month. The p-values are calculated using the adjusted-MSPE statistic of Clark and West (2007) given by:

$$f_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - [(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2]$$

Which is regressed against a constant and the test is a one-sided test.

	$120m_{\text{exp}}$	pval	$180m_{\text{exp}}$	pval	$120m_{roll}$	pval	$180m_{roll}$	pval
1m	0.008	0.013	0.027	0.004	-0.008	0.139	0.020	0.010
3m	0.080	0.000	0.087	0.000	0.077	0.000	0.079	0.000
6m	0.193	0.000	0.188	0.000	0.226	0.000	0.174	0.000
1y	0.325	0.000	0.279	0.000	0.383	0.000	0.256	0.000
2y	0.442	0.000	0.308	0.000	0.539	0.000	0.297	0.000
3y	0.420	0.000	0.169	0.000	0.526	0.000	0.291	0.000
4y	0.418	0.000	0.200	0.000	0.499	0.000	0.413	0.000
5y	0.448	0.000	0.314	0.000	0.503	0.000	0.530	0.000

Table XVIII: Macroeconomic Determinants of PC

This table shows regression results to identify the determinants of $GRNJ$, January 1990 to December 2019, 360 monthly observations. The regression is:

$$PC_t = \beta_0 + \beta_1 X_t + \varepsilon_t$$

The left hand side variable is PC_t. The right hand side predictor, X_t, is one of eight macroeconomic and fear indices which are shown in the first column of the table.

	PC_t
$NVIX_t$	0.0396
	(0.0261)
$NVIX_{SM_t}$	-0.0803
	(0.0962)
PUI_t	0.00246
	(0.00264)
$TedSpread_t$	-36.76
	(36.84)
ΔIP_t	18.37
	(21.37)
$DFSP_t$	71.13*
	(35.18)
$\Delta IPMAN_t$	8.312
	(16.93)
ΔPCE_t	-9.477
	(7.109)
Constant	-1.736***
	(0.455)
R^2_{adj}	0.211

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XIX: Predicting macroeconomic variables by the lags of PC

This table shows the results for the predictability regressions of macroeconomic variables, January 1990 to December 2019, 360 monthly observations. The regression is:

$$X_t = \beta_0 + \sum_{i=1}^{4} \beta_i PC_{t-i} + \varepsilon_t$$

The left had side variable is one of the five macroeconomic variables at the top row of the table. The right hand side predictor are the first four lags of PC.

	(1) $NVIX_t$	(2) $NVIX_{SM_t}$	(3) PUI_t	(4) $Intermediation_t$	(5) $DFSP_t$
PC_{t-1}	3.770*	0.122	17.26**	0.325*	0.00180*
	(1.858)	(0.137)	(6.574)	(0.142)	(0.000762)
PC_{t-2}	0.338	0.106	3.062	0.162	0.00146*
	(0.729)	(0.0843)	(3.040)	(0.0836)	(0.000603)
PC_{t-3}	-0.0700	-0.0808	-2.277	-0.0901	-0.000485
	(1.079)	(0.129)	(4.666)	(0.117)	(0.000309)
PC_{t-4}	-0.831	-0.00833	-4.746	-0.241	-0.00212
	(1.740)	(0.115)	(7.836)	(0.207)	(0.00115)
Constant	25.29***	1.703***	98.25***	1.455***	0.0103***
	(1.203)	(0.0818)	(9.316)	(0.287)	(0.00101)
R^2_{adj}	0.290	0.047	0.118	0.068	0.144

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XX: PC and Tail Risk

In this table, $SLOPE_t^{n\Delta} = \sigma_t^{OTM,\Delta} - \sigma_t^{ATM}$, where $\sigma_t^{OTM,\Delta}$ is the implied volatility of on out-of-the-money put option with nΔ, where n=40, 30, 20, and σ_t^{ATM} is at-the-money implied volatility. Option prices and implied volatilities are from OptionMetrics, January 1996 to December 2019. The regression of the slope of the implied volatility curve for index options against the PC index is:

$$\sigma_t^{OTM,\Delta} - \sigma_t^{ATM} = \beta_0 + \beta_1 PC_t + \beta_2 \sigma_t^{ATM} + \varepsilon_t$$

The OTM options ranges from deep out-of-the-money (20Δ) to slightly out-of-the-money (40Δ), and the at-the-money option is defined as a put option with 50Δ. The options have just under one month until expiration, and are taken on the last trading day of the month.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Slope_t^{20\Delta}$	$Slope_t^{20\Delta}$	$Slope_t^{30\Delta}$	$Slope_t^{30\Delta}$	$Slope_t^{40\Delta}$	$Slope_t^{40\Delta}$
PC_t	0.0207***	0.0216***	0.0448*	0.0467***	0.0798*	0.0832***
	(0.00501)	(0.00603)	(0.0210)	(0.0125)	(0.0388)	(0.0189)
σ_{ATM_t}		0.0500***		0.110***		0.182***
		(0.00433)		(0.00999)		(0.0182)
_cons	0.223***	0.0339*	0.512***	0.0972**	0.957***	0.267***
	(0.00595)	(0.0162)	(0.0281)	(0.0366)	(0.0554)	(0.0663)
R^2_{adj}	0.060	0.708	0.058	0.703	0.064	0.674

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XXI: Predicting International Returns

This table shows return predictability for the international equity markets, January 1990 to December 2019, 360 monthly observations. The regression equation is:

$$\frac{12}{h}\sum_{i=1}^{h} \log R_{t+i} - \log R^{f}_{t+i} = \beta_0 + \beta_1 PC_{\mathrm{t}} + \varepsilon_{t+h}$$

The panel presents the regression results for individual countries, using the respective MSCI country indices denominated in local currency. The risk-free rate for the U.K is the 3-month U.K treasury rate from FRED. The risk-free rate for Switzerland is the 3-month Swiss franc interbank rate from FRED. The risk-free rate for Japan is the interest rate on Japanese Government Tresury bills from FRED. The risk-free rate for Sweden is the 3-month Sweden Treasury rate from FRED. Standard errors are based on Newey and West (1987) HAC robust standard errors.

PC_t	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1m	3m	6m	1y	2y	3y	4y	5y
UK	0.0624**	0.0679***	0.0765**	0.0707**	0.0557***	0.0387***	0.0302***	0.0238***
	(0.0196)	(0.0200)	(0.0256)	(0.0217)	(0.0165)	(0.0117)	(0.00874)	(0.00651)
_cons	0.0380	0.0217	0.0229	0.0224	0.0205	0.0186	0.0170	0.0164
	(0.0266)	(0.0238)	(0.0235)	(0.0219)	(0.0191)	(0.0169)	(0.0149)	(0.0124)
R^2_{adj}	0.016	0.059	0.140	0.216	0.248	0.184	0.162	0.151
Switzerland	0.0547**	0.0489*	0.0573*	0.0549*	0.0446*	0.0325*	0.0269*	0.0207*
	(0.0206)	(0.0192)	(0.0242)	(0.0217)	(0.0202)	(0.0156)	(0.0120)	(0.00874)
_cons	0.0545	0.0480	0.0481	0.0481	0.0499*	0.0499*	0.0490**	0.0470***
	(0.0327)	(0.0280)	(0.0292)	(0.0251)	(0.0218)	(0.0194)	(0.0162)	(0.0131)
R^2_{adj}	0.009	0.024	0.064	0.115	0.154	0.135	0.146	0.131
Japan	0.0622*	0.0750**	0.0865**	0.0816**	0.0707**	0.0545**	0.0444**	0.0355*
	(0.0303)	(0.0288)	(0.0298)	(0.0259)	(0.0225)	(0.0200)	(0.0167)	(0.0172)
_cons	-0.00620	-0.00663	-0.00397	-0.00380	-0.00554	-0.00752	-0.00898	-0.00800
	(0.0430)	(0.0362)	(0.0326)	(0.0317)	(0.0297)	(0.0269)	(0.0241)	(0.0214)
R^2_{adj}	0.007	0.032	0.078	0.129	0.188	0.165	0.153	0.131
Sweden	0.101**	0.0806*	0.0781*	0.0653*	0.0534*	0.0380*	0.0286*	0.0207*
	(0.0382)	(0.0368)	(0.0389)	(0.0308)	(0.0251)	(0.0182)	(0.0128)	(0.00940)
_cons	0.0666	0.0482	0.0485	0.0483	0.0477	0.0474	0.0472*	0.0476*
	(0.0447)	(0.0397)	(0.0381)	(0.0333)	(0.0266)	(0.0249)	(0.0226)	(0.0186)
R^2_{adj}	0.020	0.040	0.068	0.086	0.116	0.095	0.082	0.063

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$