A Model-based Commodity Risk Measure on Commodity and Stock Market Returns[*]

Ai Jun Hou[†], Emmanouil Platanakis[‡], Xiaoxia Ye[§] and Guofu Zhou[¶]

September 2022

Abstract

We propose a novel measure of the ex-ante commodity downside-risk premium (CDP) for each commodity based on a term structure model of commodity futures. Our theory-based CDP, capturing forward-looking information in the futures markets, outperforms well-known characteristics in explaining the cross-section of commodity returns. The CDP factor – the high minus low portfolio constructed from sorting CDP – has the highest Sharpe ratio among existing factors, and none of the latter can explain it, implying it has substantial new information. Moreover, various aggregations of individual commodity CDP predict future stock market returns significantly, even after controlling for major economic predictors. The link between commodities and the stock market is stronger than previously thought.

Keywords: Commodities, Term structure models, Predictability, Cross-sectional asset pricing

[*]We are grateful to Amit Goyal, Alberto Martin-Utrera, Lin William Cong, Julian Atanassov (discussant), Yujing Gong (discussant), Rui Silva (discussant), Lars Norden, Jens Josephson, Caihong Xu, Ran Xing, Abalfazl Zareei, Yajun Xiao, Tony He, Yingying Wu, Jiatao Liu, and Chendi Zhang as well as conference participants at the 2022 Rochester Conference in Econometrics, the 2022 Annual Meeting of the European Financial Management Association (EFMA), the 2022 European Conference of the Financial Management Association (FMA Europe), the 2022 Annual Meeting of the Financial Management Association (FMA US), the 2022 Annual Conference of the Money, Macro and Finance Society (MMF), the 11^{th} International Conference of the Financial Engineering and Banking Society (FEBS), the 6^{th} Entrepreneurial Finance (ENTFIN) Annual Meeting, and seminar participants at Fudan University, Peking University, Boston College, Stockholm University, Swedish House of Finance, University of Exeter, Xi'an Jiaotong-Liverpool University and University of Bath for their useful comments and suggestions.

[†]Hou (aijun.hou@sbs.su.se) is at Stockholm Business School, Stockholm University.

[‡]Platanakis (e.platanakis@bath.ac.uk) is at University of Bath - School of Management.

[§]Ye (xiaoxia.ye@liverpool.ac.uk) is at University of Liverpool Management School.

[¶]Zhou (zhou@wustl.edu) is at Washington University in St. Louis

1 Introduction

To capture both short- and long-term information, multi-factor term structure models have long been used to study commodity futures. For example, Gibson and Schwartz (1990), Schwartz (1997), Casassus and Collin-Dufresne (2005), Trolle and Schwartz (2009), Liu and Tang (2011), and Chiang, Hughen, and Sagi (2015), among others. These studies help us understand the connection between the dynamics of commodity spot and futures on various tenors and they also provide tools to effectively transform the raw term structure of futures prices into information with meaningful economic summary statistics such as the convenience yield. Another stream of literature in studies of commodities focuses on explaining the cross-section of commodity returns, which has been developed in parallel using the well-established methodologies from the empirical asset pricing literature on the equity market. For example,Yang (2013), Gorton, Hayashi, and Rouwenhorst (2013), Szymanowska et al. (2014), and Daskalaki, Kostakis, and Skiadopoulos (2014) apply cross-sectional asset pricing tests to study factors and anomalies in the commodity market. There is also growing literature that studies the integration and co-movement between commodity and the stock market, especially on how financialization in the commodity market affects the stock market. For example, Basak and Pavlova (2016), Jacobsen, Marshall, and Visaltanachoti (2019), and Goldstein and Yang (2021) study both theoretically and empirically the predictability of the stock market based on information from commodities.

All three strands of literature are important for understanding and investing in commodity markets. Since multi-factor term structure models effectively extract deeper economic information beyond simple price-based characteristics used in traditional asset pricing tests, it is natural to ask if the information implied by a multi-factor term structure model could be useful in explaining the cross-section of commodity returns and forecasting stock market returns, which is a fundamental problem of commodity asset pricing. Moreover, whether the rich information context can improve our understanding of the link between the commodity market and the stock market. To the best of our knowledge, these important questions remain unexplored in the current literature. The answers to them from our study are *yes*.

In this paper, we bring the term structure modeling and option pricing into the commodity markets asset pricing by developing a term structure model based characteristic for individual commodities. The term structure model we adopt is a three-factor Gaussian-affine model of commodity spot price, convenience yield, and risk-free interest rate. The model closely follows Casassus and Collin-Dufresne (2005)'s framework, which has been the standard Gaussian term structure model unifying many previous models for commodity futures pricing in the literature.[1] Due to analytical solutions to affine term structure models (Dai and Singleton, 2000; Duffie, Pan, and Singleton, 2000), our model has closed-form solutions for futures, which allow us to derive analytical (up to a numerical integral) pricing formulas for the At-The-Money (ATM) binary put option, which can be interpreted as the $\mathbb{Q}$-measure (risk-neutral) probability for the commodity spot return to be negative in the next period.

We apply the *essentially* affine market price of risk specification (Duffee, 2002) to specify the $\mathbb{P}$-measure (physical) dynamics of the three factors. We estimate the model using Kalman Filter in conjunction with Maximum Likelihood Estimation (MLE), which is the standard estimation method for term structure models with latent factors (see, e.g., Babbs and Nowman, 1999). We apply our model to a comprehensive set of 29 commodity futures in all four markets: Agriculture, Energy, Livestock, and Metals, with daily term structure data of futures prices and US Treasury bill yields (from maturities up to 12 months). The full sample period is from March 1990 to March 2021. To avoid the look-into-future bias, we re-estimate the model in each month using data only up to the estimation month in an expanding window.

Based on the estimated model for each commodity, we infer the prices for the ATM binary put option under both the $\mathbb{Q}$ and the $\mathbb{P}$ measures. The difference between them indicates the compensation to risk in terms of probability. Since the expectations are for put option payoffs, the implied premium is for the downside risk. Hence, it serves as our measure of commodity downside risk premium (CDP) for the underlying commodity, similar

[1] The models nested in Casassus and Collin-Dufresne (2005)'s framework include: Gibson and Schwartz (1990), Brennan (1991), Schwartz (1997), Ross (1997), and Schwartz and Smith (2000).

to how the variance risk premium is defined in the literature (see, e.g., Bollerslev, Tauchen, and Zhou, 2009; Bekaert and Hoerova, 2014; Cheng, 2019). By definition, CDP has a support within -1 to 1, making it comparable across commodities. Our analytical results also reveal that the basis defined as the log difference between spot and futures prices is positively related to the ATM binary put option price, i.e., the $\mathbb{Q}$-measure probability of the next period return being negative. This means that the basis only partially captures the downside risk premium as it ignores the physical downside risk. Therefore, CDP is a theoretically improved predictor over the basis for future commodity returns. In addition, our measure is ex-ante because we assume that it can be time-varying and we use the forward-looking futures data to estimate it. In contrast, many measures of risk premia, such as factor risk premia, reply on sample means of the data, which is often applied ex-post and assumes a constant premium.

The individual CDPs exhibit strong heterogeneity across commodities. Using Principal Components Analysis (PCA), we find that the total variation in CDPs among all commodities cannot be hardly explained by a small set of principal components. This observation is consistent with Daskalaki, Kostakis, and Skiadopoulos (2014) who find that the commodity markets are considerably heterogeneous. The heterogeneity indicates there are rich information contents contained in CDP that could be useful for asset pricing tests and stock market prediction.

We examine asset pricing implications by first considering quartile portfolios sorting by CDP. Since CDP measures the downside risk premium of individual commodities, higher returns are expected for taking long (short) positions on commodities with more positive (negative) downside risk premiums. Therefore, we expect the High minus Lower (H-L) portfolio, which we term CDP factor, would deliver significantly positive returns on average. Indeed, our empirical results provide strong evidence supporting this hypothesis. More concretely, our CDP factor delivers an average monthly return of 0.87% with a t-statistic of 2.63. They significantly outperform the H-L portfolios sorted by other commonly used benchmark risk measures, such as the basis and momentum (Szymanowska et al., 2014). The alpha coefficients of our H-L portfolio are positive and significant in all regressions controlled for a wide range of factors including: the basis (Szymanowska et al., 2014), momentum, commodity market (average returns of all commodities' front month futures), carry (Koijen et al., 2018), and Fama-French five factors, suggesting that none of the well-known factors is able to explain the returns of the H-L portfolio. We also estimate Lettau, Maggiori, and Weber (2014) downside risk beta for our CDP factor and find it is not significant, indicating that CDP factor cannot be explained by the equity market downside risk factor in the existing literature. In addition, in terms of factor investing, our CDP factor has the greatest Sharpe ratio among existing factors.

Recent studies predict that the integration and co-movement between commodity and stock markets should be strong due to the prevailing financialization of commodities.[2] In particular, the theoretical studies of Basak and Pavlova (2016) and Goldstein and Yang (2021) show that the large inflow of financial capital from other financial markets should make the segmented commodity futures markets become more integrated with financial markets. In a survey paper, Cheng and Xiong (2014) show that correlations of commodity prices with prices in other asset classes, especially the stock market, have noticeably increased after 2000 (see, e.g., their Figure 3).

Despite the linkage, the existing evidence on the predictive power of commodity returns on stock market returns has been underwhelming and mixed (see, e.g., Huang, Masulis, and Stoll, 1996; Black et al., 2014; Jacobsen, Marshall, and Visaltanachoti, 2019). Since the CDPs capture the risk premia of commodities, as shown by the high Sharp ratio of the CDP factor, the greater they are, the more risk the buyers of commodities have to take. As commodities are mostly inputs of the firm productions in the economy, the investors will take a greater risk too. As a result, we expect the CDPs positively predict the stock market returns. However, since there are 29 CDPs, we need an efficient way to aggregate the information before applying the standard predictive regression model to predict the market.[3]

[2] Institutional investors entering commodity futures markets is referred to as the financialization of commodities.

[3] See, e.g., Rapach and Zhou (2022), for a recent survey of the literature on market predictability and the importance of information aggregation.

We use the Partial Least Square (PLS) method of (Kelly and Pruitt, 2013, 2015) as our primary aggregation method to construct an aggregate predictor from the $N = 29$ individual CDPs, and denote the predictor as CDP^{PLS}. The underlying assumption of the PLS is that the true predictor is unobservable, and each commodity characteristic is a proxy of it. Statistically, our main target is to extract an aggregate predictor from its underlying proxies related only to stock returns by removing individual noises irrelevant to stock returns. As an alternative, we also use a recently developed aggregation method, the scaled principal component analysis (sPCA) of Huang et al. (2022), to construct another aggregate predictor CDP^{sPCA}. The idea of sPCA, is to assign more weight to those important individual predictors that have more power in forecasting future returns. In addition, we also consider a simple average combination of CDP^{PLS} and CDP^{sPCA}, denoted as CDP$^{PLS+sPCA}$. We use this for both in- and out-of-sample predictions.

We find that the in-sample R^2's of CDP^{PLS}, CDP^{sPLS}, and CDP$^{PLS+sPCA}$ are 4.30%, 3.06%, and 3.78%, respectively, with significantly positive slopes in the predictive regressions of monthly excess returns of the stock market on the aggregate predictors for the period from February 1994 to March 2021. In addition, all the three aggregate CDP predictors maintain their strong predictability after controlling for the economic variables used by Welch and Goyal (2008), the investor sentiment index of Huang et al. (2015), the short interest index of Rapach, Ringgenberg, and Zhou (2016), the corresponding aggregate predictors constructed with economic variables by using PLS ($ECON^{PLS}$), sPCA ($ECON^{sPCA}$) and PLS+sPCA ($ECON^{PLS+sPCA}$), as well as a wide variety of uncertainty variables, suggesting that they contain unique information for forecasting the stock market.

For the out-of-sample analysis, we use both the R^2_{OS} metric of Campbell and Thompson (2008) and the mean squared forecasting errors (MSFE)-adjusted statistic of Clark and West (2007). By initiating a 20-year expanding estimation window, we show that CDP^{PLS}, CDP^{sPLS}, and CDP$^{PLS+sPCA}$ generate economically sizable out-of-sample R^2_{OS}'s across prediction horizons of up to two years, which are statistically significant in most cases. In contrast to the aggregate CDP predictors, $ECON^{PLS}$, $ECON^{sPLS}$ and $ECON^{PLS+sPLS}$ mostly generate negative R^2_{OS}'s. These results indicate that through the lens of the term structure model, more forward-looking information than the commodity returns per se can be extracted for effectively predicting stock index returns, confirming the theoretical predictions by Basak and Pavlova (2016) and Goldstein and Yang (2021) regarding the interconnection between the commodity markets and the stock market.

We show that mean-variance investors can obtain substantial investment gains from an asset allocation perspective by using the three aggregate CDP predictors. For a typical risk aversion coefficient of five, the annualized certainty equivalent return (CER) gains at the monthly horizon, with no transaction costs, by using CDP^{PLS}, CDP^{sPLS} and $\text{CDP}^{PLS+sPLS}$ are 1.25%, 0.36%, and 1.46%, respectively. The investment gains also remain sizable when considering transaction costs in most cases. In contrast, aggregate predictors based on economic variables mostly generate negative CER gains. In addition, investment portfolios based on aggregate CDP predictors generate large Sharpe ratios and outperform the corresponding portfolios that use aggregate predictors constructed with economic variables.

We further examine whether the out-of-sample forecasting performance of CDP aggregate indices is robust by using alternative econometric and machine learning methods. By considering the combination ENet (C-ENet) of Dong et al. (2022), the simple (average) combination forecast of the individual univariate forecasts, and the Ridge shrinkage regression of Hoerl and Kennard (1970), we show that all these alternative methods produce economically sizable out-of-sample R^2_{OS}'s across prediction horizons, while all the R^2_{OS}'s generated by C-ENet and Ridge are statistically significant across prediction horizons according to the MSFE-adjusted statistics.

Finally, we investigate further why the CDP indices predict stock market returns. Cochrane (2011) shows that if a variable can predict market returns its predictive power must come from predicting cash flow news or/and discount rate news. We study hence if the CDP indices' predictability comes from the discount rate channel or cash flow channel. We find convincing evidence supporting the cash flow channel, consistent with the prediction of the finalization theory, e.g., Basak and Pavlova (2016) and Goldstein and Yang (2021). We also study how the CDP indices are related to the macroeconomy. Our results show that the CDP indices add incremental predictive power to the inflation rate beyond that from its own past data, validating the predictability of the CDP indices on stock returns from a macro perspective.

Our paper contributes to the joint venue of three important strands of literature: a) Term structure of futures modeling and option pricing for commodities. In a pioneering study, Gibson and Schwartz (1990) develops and empirically tests a two-factor term structure model for pricing financial and real assets contingent on the price of oil. This two-factor model is subsequently enhanced in Schwartz (1997) by allowing mean-reverting in both spot price and convenience yield. Casassus and Collin-Dufresne (2005) unify the previous models into a three-factor Gaussian affine model with maximal flexibility in the sense of Dai and Singleton (2000). There are further works extending the framework to incorporate stochastic volatility, e.g., Trolle and Schwartz (2009), Liu and Tang (2011), and Chiang, Hughen, and Sagi (2015).

b) Asset pricing of cross-sectional commodity returns. This literature focuses on explaining the cross-section of commodity returns using well-established methodologies from the empirical asset pricing in the equity market. For example, Szymanowska et al. (2014) and Yang (2013) find the commodity basis has pricing power in the cross-section of commodity portfolios. Daskalaki, Kostakis, and Skiadopoulos (2014) and Bakshi, Gao, and Rossi (2019) show momentum also has asset pricing implications in the commodity markets. Other factors such as commodity market average returns, inventory, and hedging pressure have also been proposed (see, e.g., Erb and Harvey, 2006; De Roon, Nijman, and Veld, 2000; Gorton, Hayashi, and Rouwenhorst, 2013).

c) Stock market return prediction. Welch and Goyal (2008) examine the performance of variables that have been suggested as good predictors of the equity premium and find that these variables have poor performance both in-sample and out-of-sample. Ferreira and Santa-Clara (2011) propose the sum-of-the-parts (SOP) method and use it to forecast stock market returns out of sample, they find that the SOP method produces statistically and economically significant gains and performs better than the historical mean. Huang et al. (2015) apply the partial least square method to traditional investor sentiment proxies and construct an aligned investor sentiment index that has strong predictive power on the aggregate stock market returns. Jiang et al. (2019) find a sentiment index based on the aggregated textual tone of corporate financial disclosures that is a strong negative predictor of future aggregate stock market returns. Jacobsen, Marshall, and Visaltanachoti (2019) empirically show that industrial metals such as copper and aluminum predict stock market returns. Using various shrinkage techniques, Dong et al. (2022) provide evidence on the link between long-short anomaly portfolio returns and the predictability of the aggregate market returns based on 100 representative anomalies from the literature.

We extend existing term structure modeling with option pricing components and develop CDP for individual commodities, contributing to (a). We show that CDP has a natural interpretation of downside risk premium and strong explanatory power for the cross-section of individual commodity returns, contributing to (b). We also confirm that an aggregate index constructed from the individual CDP has strong predictive power for the stock market returns that complement the role of other typical economic predictors, contributing to (c).

The remainder of the paper is organized as follows. Section 2 presents the model and develops CDP. Section 3 describes the data, model estimation, and summary of CDP. Sections 4 and 5 present the empirical results on the cross-sectional asset pricing of commodity returns and predicting stock market returns, respectively. Finally, section 6 concludes the paper. Appendices contain technical details and supplementary results.

2 Term structure model for futures and option pricing

2.1 Commodity futures

We follow Casassus and Collin-Dufresne (2005)'s framework and set up a three-factor $\{r, \delta, X\}$ system to model the log spot commodity price, where r is the risk-free interest rate, δ is the convenience yield, and X is the log spot commodity price. We start from the specification of the risk-neutral $\mathbb{Q}$-measure dynamic.

$$dr_t = \kappa_r \left(\bar{r} - r_t\right) dt + \sigma_r dz_{r,t}^{\mathbb{Q}}, \tag{2.1}$$

$$d\delta_t^0 = \kappa_\delta \left(\bar{\delta} - \delta_t^0\right) dt + \sigma_\delta dz_{\delta,t}^{\mathbb{Q}}, \tag{2.2}$$

$$dX_t = \left[r_t - \left(\delta_t^0 + \alpha_r r_t + \alpha_X X_t\right) - \frac{1}{2}\sigma_X^2\right] dt + \sigma_X dz_{X,t}^{\mathbb{Q}}, \tag{2.3}$$

where $z_{r,t}^{\mathbb{Q}}$, $z_{\delta,t}^{\mathbb{Q}}$, and $z_{X,t}^{\mathbb{Q}}$ are three correlated Wiener processes under the $\mathbb{Q}$-measure. Under this specification, the convenience yield δ_t is a linear combination of δ_t^0, r_t and X_t, i.e., $\delta_t = \delta_t^0 + \alpha_r r_t + \alpha_X X_t$. Under the $\mathbb{Q}$-measure, the drift term of X_t is $r_t - \delta_t - \frac{1}{2}\sigma_X^2$ which ensures the arbitrage-free pricing of the futures price. Therefore, we can price the time t futures maturing at T, $F_t(T)$, as the conditional expectation of $\exp\left(X_T\right)$ under the $\mathbb{Q}$-measure:

$$F_t(T) = \mathbb{E}_t^{\mathbb{Q}}(e^{X_T}).$$

For notations convenience, we rewrite the three-factor system in the matrix form. Denote Y_t as $[r_t, \delta_t, X_t]^\intercal$:

$$dY_t = (K_0 + K_1 Y_t)dt + \sqrt{\Sigma} dZ_t^{\mathbb{Q}}, \tag{2.4}$$

where $Z_t^{\mathbb{Q}}$ is an IID 3×1 Wiener processes vector under the $\mathbb{Q}$-measure, and

$$\underbrace{K_0}_{3\times 1} = \begin{bmatrix} \kappa_r \bar{r} \\ \kappa_\delta \bar{\delta} \\ -\frac{\sigma_X^2}{2} \end{bmatrix}, \underbrace{K_1}_{3\times 3} = \begin{bmatrix} -\kappa_r & 0 & 0 \\ 0 & -\kappa_\delta & 0 \\ 1 - \alpha_r & -1 & -\alpha_X \end{bmatrix}, \underbrace{\Sigma}_{3\times 3} = \begin{bmatrix} \sigma_r^2 & \sigma_r \sigma_\delta \rho_{r\delta} & \sigma_X \sigma_r \rho_{Xr} \\ \sigma_r \sigma_\delta \rho_{r\delta} & \sigma_\delta^2 & \sigma_X \sigma_\delta \rho_{X\delta} \\ \sigma_X \sigma_r \rho_{Xr} & \sigma_X \sigma_\delta \rho_{X\delta} & \sigma_X^2 \end{bmatrix}$$

The system of (2.4) is a multivariate Gaussian process, the affine techniques developed in Duffie, Pan, and Singleton (2000), Dai and Singleton (2000), and Casassus and Collin-Dufresne (2005) can be readily applied to solve the futures price, $\mathbb{E}_t^{\mathbb{Q}}\left(e^{X_{t+\tau}}\right)$. Specifically, we have:

$$\mathbb{E}_t^{\mathbb{Q}}\left(e^{X_{t+\tau}}\right) = \mathbb{E}_t^{\mathbb{Q}}\left(e^{\iota^\intercal Y_{t+\tau}}\right) = e^{A(\tau) + B(\tau)^\intercal Y_t},$$

and $A(\tau)$ and $B(\tau)$ satisfy the following system of ODEs

$$\frac{\partial B(\tau)}{\partial \tau} = K_1^{\intercal} B(\tau) \tag{2.5}$$

$$\frac{\partial A(\tau)}{\partial \tau} = K_0^{\intercal} B(\tau) + \frac{1}{2} B(\tau)^{\intercal} \Sigma B(\tau) \tag{2.6}$$

with boundary conditions $B(0) = \iota$ and $A(0) = 0$. From (2.5), we have:

$$B(\tau) = \exp(K_1^{\intercal}\tau)\iota.$$

Given $B(\tau)$, from (2.6) we obtain:

$$A(\tau) = \frac{\iota^{\intercal}\left[\int_0^{\tau} \exp(K_1 s)\, \Sigma \exp(K_1^{\intercal} s)\, ds\right]\iota}{2} + \iota^{\intercal}\left[\exp(K_1\tau) - I\right] K_1^{-1} K_0.$$

In summary, the futures prices can be written as:

$$F_t(t + \Delta t) = e^{\frac{\iota^{\intercal}\Omega(K_1,\Delta t)\iota}{2} + \iota^{\intercal}[\exp(K_1\Delta t) - I]K_1^{-1}K_0 + \iota^{\intercal}\exp(K_1\Delta t)Y_t}, \tag{2.7}$$

where $\iota = [0, 0, 1]^{\intercal}$, I is the identity matrix, and

$$\Omega(K_1, \Delta t) = \int_0^{\Delta t} \exp(K_1 s)\, \Sigma \exp(K_1^{\intercal} s)\, ds.$$

2.2 Option pricing and CDP

Under this setting, we consider the price of a τ-maturity At-The-Money (ATM) binary put option with the payoff being one if $X_{t+\tau} < X_t$ and zero otherwise.[4] By Proposition 2 in

[4] Rigorously speaking the option's pricing should be $\mathbb{E}_t^{\mathbb{Q}}\left(e^{-\int_t^{t+\tau} r_s ds}\mathbb{1}_{\{X_{t+\tau}<X_t\}}\right)$. Since we only consider $\tau =$ one month in our empirical study, the difference is negligible.

Duffie, Pan, and Singleton (2000), we have:

$$\mathbb{E}_t^{\mathbb{Q}}\left(\mathbb{1}_{\{X_{t+\tau}<X_t\}}\right) = \frac{1}{2} - \frac{1}{\pi}\int_0^{\infty} \frac{\exp\left(-\frac{v^2\iota^{\intercal}\Omega(K_1,\tau)\iota}{2}\right)\mathbf{Im}\left\{\exp\left[iv\begin{pmatrix}\iota^{\intercal}\left[\exp(K_1\tau)-I\right]K_1^{-1}K_0\\ +\iota^{\intercal}\exp(K_1\tau)Y_t - X_t\end{pmatrix}\right]\right\}}{v}dv$$

$$= \frac{1}{2} - \frac{1}{\pi}\int_0^{\infty}\exp\left(-\frac{v^2\iota^{\intercal}\Omega\left(K_1,\tau\right)\iota}{2}\right)\sin\left[v\iota^{\intercal}\begin{pmatrix}\left[\exp(K_1\tau)-I\right]K_1^{-1}K_0\\ +\exp(K_1\tau)Y_t - Y_t\end{pmatrix}\right]/v\,dv$$

$$= \frac{1}{2} - \frac{1}{\pi}\int_0^{\infty}\exp\left(-\frac{v^2\iota^{\intercal}\Omega\left(K_1,\tau\right)\iota}{2}\right)\sin\left[vG(K_0,K_1,\tau,Y_t)\right]/v\,dv \tag{2.8}$$

where $\mathbf{Im}(c)$ denotes the imaginary part of c, and

$$G(K_0,K_1,\Delta t,Y_t) = \iota^{\intercal}\left[\exp(K_1\Delta t)-I\right]\left(K_1^{-1}K_0+Y_t\right).$$

By definition, the price of the ATM binary put option $B_t^{\mathbb{Q}}(t+\Delta t) = \mathbb{E}_t^{\mathbb{Q}}\left(\mathbb{1}_{\{X_{t+\Delta t}<X_t\}}\right)$. When valued using information calibrated from the commodity futures, $B_t^{\mathbb{Q}}(t+\Delta t)$ has a natural economic interpretation: it measures the market assessment of the downside risk implicit in the term structure of the commodity futures prices, as (2.8) is the $\mathbb{Q}$ measure the probability of the spot price at time $t+\Delta t$ being lower than the current spot price at time t.

We follow Duffee (2002)'s *essentially* affine market price of risk specification and specify the SDE of Y_t under the physical $\mathbb{P}$-measure as[5]

$$dY_t = (K_0^{\mathbb{P}} + K_1^{\mathbb{P}}Y_t)dt + \sqrt{\Sigma}dZ_t^{\mathbb{P}}. \tag{2.9}$$

Given (2.9), we define the $\mathbb{P}$ measure probability of the spot price at time $t+\Delta t$ being

[5]This specification imposes zero correlation across commodities on the correlation structure of the vector of Wiener processes under the $\mathbb{P}$-measure. This allows us to avoid an intractable joint estimation with all commodities and estimate the model for individual commodities separately. As shown in Casassus and Collin-Dufresne (2005), relaxing this restriction offers little improvement in the model estimation.

lower than the current spot price at time t as:

$$B_t^{\mathbb{P}}(t+\varDelta t) = \mathbb{E}_t^{\mathbb{P}}\left(\mathbb{1}_{\{X_{t+\varDelta t}<X_t\}}\right) \tag{2.10}$$

$$= \frac{1}{2} - \frac{1}{\pi}\int_0^\infty \frac{\exp\left(-\frac{v^2 \iota^\intercal \varOmega\left(K_1^{\mathbb{P}},\varDelta t\right)\iota}{2}\right)\sin\left[vG(K_0^{\mathbb{P}},K_1^{\mathbb{P}},\varDelta t,Y_t)\right]}{v}dv. \tag{2.11}$$

By definition, $B_t^{\mathbb{P}}(t+\varDelta t)$ measures the physical (statistical) downside risk implied by the historical dynamics of the commodity futures prices. Our model-based commodity characteristic, which we refer to as Commodity Downside-risk Premium (CDP), is defined as the difference between $B_t^{\mathbb{Q}}(t+\varDelta t)$ and $B_t^{\mathbb{P}}(t+\varDelta t)$:

$$\mathrm{CDP}_t(\varDelta t) = B_t^{\mathbb{Q}}(t+\varDelta t) - B_t^{\mathbb{P}}(t+\varDelta t). \tag{2.12}$$

$\mathrm{CDP}_t(\varDelta t)$ has a natural risk premium interpretation. This is similar to the way premium is defined in the variance risk premium literature (see, e.g., Bollerslev, Tauchen, and Zhou, 2009). By definition, CDP_t's support is within -1 to 1, which makes it naturally comparable cross commodities and an ideal measure to be used for index construction.

2.3 Downside risk interpretation of the basis

The basis in the commodity literature is often defined as the log difference between spot and near maturity futures prices (Yang, 2013; Daskalaki, Kostakis, and Skiadopoulos, 2014), i.e., $\mathrm{Basis}_t = X_t - \log F_t(t+\varDelta t)$.

In the light of (2.7), (2.8) can be rewritten as a function of the basis:

$$B_t^{\mathbb{Q}}(t+\varDelta t) = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty e^{-\frac{v^2\iota^\intercal\varOmega(K_1,\varDelta t)\iota}{2}}\sin\left[v\left(\mathrm{Basis}_t + \frac{\iota^\intercal\varOmega\left(K_1,\varDelta t\right)\iota}{2}\right)\right]/v\,dv. \tag{2.13}$$

From (2.13), we can see that the market assessment of the downside risk $B_t^{\mathbb{Q}}(t+\varDelta t)$ clearly increases with the basis. This theoretical finding is in-line with those in Szymanowska et al. (2014) and Gorton, Hayashi, and Rouwenhorst (2013) who infer from their models that the basis contains information about the spot risk premium. As shown above, the clean measure of risk premium is $\mathrm{CDP}_t(\Delta t)$ in (2.12). Therefore, even though the basis contains information about the risk premium, it only measures the total price ($\mathbb{Q}$-expectation) of downside risk that does not offset the $\mathbb{P}$-measure downside risk. Given the theoretical superiority of our risk premium measure over the basis, we expect CDP_t to have better performance in commodity asset pricing tests than the basis and other price-based measures, e.g., the momentum.

3 Data and model estimation

3.1 Data

We use the daily data on 29 individual commodity futures contracts from Refinitiv. The names and types are summarized in Table 1. The futures maturities range from one month to 12 months (with a few exceptions up to 18 months in the early part of the sample). The data sample covers period from March 1990 to March 2021. We reserve the data from March 1990 to December 2000 for initial model estimation and study the asset pricing implications using the data from January 2001 to March 2021 where all model outputs are out-of-sample estimates. We plot the cross-sectional distribution of the monthly total returns (start from January 2001 as one) of the front-month futures in Figure 1. The summary statistics of the front-month monthly returns during the same period are presented in Table 1. To estimate the parameters of the risk-free interest rate model, we also use four-week, three-month, six-month, and one-year Treasury bill yields data downloaded from Federal Reserve Economic Data at the Federal Reserve Bank of St. Louis. The sample period of the Treasury bill yields is matched with that of the commodity futures data.

[*Insert Table 1 and Figure 1 about here*]

3.2 Kalman filter and maximum likelihood estimation

Consistent with Casassus and Collin-Dufresne (2005), we set:

$$K_0^{\mathbb{P}} = \begin{bmatrix} \alpha_r^{\mathbb{P}} \\ \alpha_\delta^{\mathbb{P}} \\ \alpha_X^{\mathbb{P}} \end{bmatrix} \text{ and } K_1^{\mathbb{P}} = \begin{bmatrix} \beta_r^{\mathbb{P}} & 0 & 0 \\ 0 & \beta_\delta^{\mathbb{P}} & 0 \\ \beta_{rX}^{\mathbb{P}} & \beta_{\delta X}^{\mathbb{P}} & \beta_X^{\mathbb{P}} \end{bmatrix}.$$

This setting ensures that the short rate follows an autonomous Ornstein-Uhlenbeck (OU) process under both $\mathbb{P}$ and $\mathbb{Q}$ measures, and the component of the convenience yield (δ_t^0) is linearly independent of interest rate and spot price level under $\mathbb{Q}$ measures remains so under the $\mathbb{P}$ measure.

Since the log of the futures price is an affine function of the state variables, we can employ the Kalman filter (KF) in conjunction with MLE for the model estimation (see, e.g., Babbs and Nowman, 1999; De Jong, 2000). Details of the KF are given in Appendix A. We discretize and re-write the model in state space form, and use log of the futures price as the measurement equation. Specifically, the state space representation is:

$$Y_t = \left[\exp(K_1^{\mathbb{P}} h) - I\right] \left(K_1^{\mathbb{P}}\right)^{-1} K_0^{\mathbb{P}} + \exp(K_1^{\mathbb{P}} h) Y_{t-h} + \sqrt{\Omega\left(K_1^{\mathbb{P}}, h\right)}\epsilon_t, \quad \epsilon_t \sim \mathrm{IID}\boldsymbol{\mathcal{N}}\left(0, I_{3\times 3}\right)$$

Transition Equation

$$\log\left(\overline{F}_t^{\Delta t}\right) = \frac{\iota^\intercal \Omega\left(K_1, \Delta t\right)\iota}{2} + \iota^\intercal\left[\exp(K_1 \Delta t) - I\right] K_1^{-1} K_0 + \iota^\intercal \exp(K_1 \Delta t) Y_t + \xi_t, \quad \xi_t \sim \mathrm{IID}\boldsymbol{\mathcal{N}}\left(0, sI_{n_t \times n_t}\right),$$

Measurement Equation

where h is the time interval (one day), ξ_t is the measurement error on day t, and n_t is the number of futures on day t. The measurement $\log\left(\overline{F}_t^{\Delta t}\right)$ consists of log of all available futures (with various time to maturities) close prices observed on day t. Given the normally distributed measurement error, the distribution of $\log\left(\overline{F}_t^{\Delta t}\right)$ conditional on the information set $\boldsymbol{\mathcal{F}}_{t-h}$ is a multi-dimensional normal distribution with the mean $\log\left(\overline{F}_{t|t-h}^{\Delta t}\right)$ and covariance matrix $P_{\log\left(\overline{F}_t^{\Delta t}\right)}$. Thus, the transition density of $\log\left(\overline{F}_t^{\Delta t}\right)$ can be written as:

$$p_t = \left[(2\pi)^{\frac{n_t}{2}}\left|P_{\log\left(\overline{F}_t^{\Delta t}\right)}\right|^{\frac{1}{2}}\right]^{-1}$$
$$\exp\left\{-\frac{1}{2}\left[\log\left(\overline{F}_t^{\Delta t}\right)-\log\left(\overline{F}_{t|t-h}^{\Delta t}\right)\right]^{\intercal}P^{-1}_{\log\left(\overline{F}_t^{\Delta t}\right)}\left[\log\left(\overline{F}_t^{\Delta t}\right)-\log\left(\overline{F}_{t|t-h}^{\Delta t}\right)\right]\right\},$$

where $\log\left(\overline{F}_{t|t-h}^{\Delta t}\right)$ and $P_{\log\left(\overline{F}_t^{\Delta t}\right)}$ are outputs from the Kalman filter update. Then the log-likelihood function is given by:

$$\ln\mathscr{L} \propto -\sum_{t=1}^{N}\log\left(p_t\right).$$

where N is the total number of days in the sample. Please note that the parameters of the risk-free interest rate r_t cannot be identified using only futures prices, they need to be estimated separately using the Treasury yields data (Casassus and Collin-Dufresne, 2005). Since the interest rate is modelled as a one-factor OU process, it is essentially the Vasicek (1977) model.[6] The same estimation method above can be applied to estimate the parameters of r_t using the Treasury yield data.

To make sure the CDP estimates are ex-ante without look-ahead bias, we conduct an expending window out-of-sample estimation. More concretely, we re-estimate the model each month after adding one month of daily data to the sample in each estimation. Each month we use the KF based on the previous month's model parameters to filter out state variables from the futures prices and compute the CDPs. Since we use monthly returns in the asset pricing tests, we compute the CDP with Δt = one month. Hereafter, all referred CDPs are associated with Δt = one month unless stated otherwise explicitly.

3.3 Summary of the characteristics

In Figure 2, we plot the cross-sectional distribution of the CDPs in the four types of commodities from 2001 to 2021. On average, the CDPs are slightly negative after 2006, espe-

[6] The details of the model can also be found in Casassus and Collin-Dufresne (2005, Appendix B).

cially so during the 2008 financial crisis. Looking at the aggregate level in the four types individually, the CDPs in Agriculture (Energy) are more negative (positive), while those in Livestock and Metals are closer to zero with higher volatility found in Livestock than in Metals. Cross-sectionally, Agriculture, and Energy exhibit more cross-sectional variation than Livestock and Metals over the years. It is worth noting that in Energy there is a shock to the cross-section of the CDPs from 2014 to 2016, which corresponds to the steep plunge in the oil price during this period (Friedman, 2014). This large spike in the cross-sectional dispersion in the CDPs reflects the unprecedented uncertainty shock. The differential cross-sectional variation among the commodities over time alongside its unified support within -1 and 1 make the individual CDP a great characteristic to conduct asset pricing tests in the commodity markets.

[*Insert Figure 2 about here*]

3.4 Principal component analysis

In this subsection, we carry out the Principle Component Analysis (PCA) on the panel the CDP estimates. The results show that the total variation in the CDPs cannot be explained by a small set of common components.

Due to that missing data in several CDPs before 2000, we perform the PCA based on the out-of-sample period, starting from January 2001 to March 2021.

[*Insert Figure 4 about here*]

Figure 4 plots the variation of the 29 CDPs explained by the first 10 PCs. From the plot, we see that none of the PCs can catch up the large variations in the panel of the CDPs. The first, second, and third PCs only explain 36%, 14% and 8%, respectively, of the total variation. The remaining PCs hardly have explanatory power more than 5%. All 10 PCs together can only explain less than 90% of the total variation.

Next, we examine if there is any commonality in factor loadings of the CDPs on these PCs. We run time series regressions (regressing all 29 CDPs on the first five PCs) and collect the loading coefficients. A summary of these coefficients is presented in Table 2.

[*Insert Table 2 about here*]

From Table 2, we find that there is no clear pattern can be found in the loading coefficients' distribution, neither at the individual level nor at the sector level. All the loading estimates are small on average and with sizable cross-sectional standard deviations.

In general, we conclude that no small set of common factors can explain the overall variation in the panel of the CDPs. This observation is consistent with Daskalaki, Kostakis, and Skiadopoulos (2014) who find that the commodity markets are considerably heterogeneous.

4 Commodity asset pricing

4.1 Portfolio sorting

Since the CDP measures the downside risk premium of individual commodities, a positive CDP indicates that investors are willing to pay more to avoid the downside risk. More concretely, the CDP is the difference between the market value of the ATM binary put option and its actuarial value. The higher CDP, the more investors are willing to pay for the put beyond what can be justified by its physical risk. Taking long positions in a commodity is somewhat analogous to writing put options for this commodity. Therefore, when a commodity's CDP is high (low), positive returns are expected for taking long (short) positions on this commodity. Given this insight, we expect the CDP factor, which is the High minus Lower portfolio based on the CDP, would deliver significantly positive returns on average.

We form quartile portfolios using all 29 commodity front month futures returns based on the CDPs at a one-month horizon.[7] The formation period is one day before the start of the one-month holding period. The portfolios are rebalanced at the end of each month. The portfolio sorting results are presented in Table 3. For benchmarking purposes, we also form portfolios based on the basis (the difference between the log of front-month futures and the log of second-month futures on the formation period) and the momentum (the past

[7] The results from quintile portfolios deliver the same message. The results are presented in the Online Appendix.

one-year cumulative return on the formation period). These two benchmarks have been commonly studied in the previous commodity asset pricing literature, e.g., Yang (2013), Szymanowska et al. (2014), and Daskalaki, Kostakis, and Skiadopoulos (2014).

[*Insert Table 3 about here*]

From Table 3, we can see that in the full sample (January 2001 to March 2021), only the CDP factor shows significant returns: an average monthly return of 0.87% with t statistic = 2.63, while Basis and Momentum produces insignificant returns: an average monthly return of 0.29% (t statistic = 0.84) for Basis and 0.02% (t statistic = 0.04) for Momentum. To further understand the difference between the performance of the CDP factor and the benchmarks, we also conduct a subsample analysis. In the first half sample (January 2001 to May 2011), we find the CDP factor and Basis portfolios have similar performance and they all deliver significant returns: an average monthly return of 0.93% (t statistic = 1.98) for CDP and 0.94% (t statistic = 1.91) for Basis. Although insignificant, the Momentum portfolios also deliver a sizeable average monthly return of 0.76% (t statistic = 1.36). The benchmark results from the first half sample confirm the findings documented in the previous studies using data before 2011. However, when looking at the second half of the sample, we see a different picture. Although less significant than the first half and the full sample returns, the CDP factor produces a significant average monthly return of 0.82% (t statistic = 1.73). In contrast, the average monthly returns from both the Basis and Momentum portfolios turn negative and insignificant (-0.4% with t statistic = -0.84 for Basis and -0.76% with t statistic = -1.43 for Momentum). These observations show that the significant pricing power of Basis and Momentum documented in the previous literature disappears in the recent 10 years of data, while the CDP factor has robust performance in both samples. These observations become even clearer when we plot out the cumulative returns of the three portfolios over time. The time series are shown in Figure 3. Before 2015, the cumulative returns of all three portfolios have a clear upward trajectory. After 2015, the CDP factor continues with its upward trajectory, while the two benchmarks diverge from the CDP factor and develop into clear downward trajectories.

[*Insert Figure 3 about here*]

4.2 Potential explanations for the CDP factor

By eyeballing Figure 3, we can also easily tell that the CDP factor can harly be explained by the Basis or Momentum factor. We verify this conjecture by following the standard asset pricing practice and examining the alpha coefficients from regressing the CDP factor on various other factors. These factors include: Basis, Basis High and Low portfolios, Momentum, commodity market portfolio, commodity carry factor (Koijen et al., 2018) and Fama-French five factors (Fama and French, 2015). Here, the Basis and Momentum are the High-Low portfolios. We also include the separate Basis High and Basis Low portfolios as another control considering the fact that Szymanowska et al. (2014) show that in addition to the Basis H-L's explanatory power on commodity futures' spot premia, the two separate portfolios can explain commodity futures' term premia. The results are shown in the left panel of Table 4. From the results, we can clearly see all alpha coefficients are significant on at least 5% level, indicating none of these factors is able to explain our CDP factor.

[*Insert Table 4 about here*]

Since the CDP has a natural interpretation of downside risk premium, we explore whether common downside risk can explain the CDP factor. Lettau, Maggiori, and Weber (2014) (LMW) propose a downside risk CAPM in which expected returns are driven by the market beta conditional on low returns. Following Koijen et al. (2018), we examine the CDP factor downside risk exposure by checking the significance of its LMW downside risk beta. The LMW downside risk beta is estimated by conditionally regressing the CDP factor on the stock market returns when the market returns are one standard deviation below their sample mean. For comparison, we also apply the same estimation to the Basis, Momentum, and commodity market portfolios. The results are reported in Table 5.

[*Insert Table 5 about here*]

The downside risk betas are significant for the Basis (at 10% level) and commodity market (at 1% level) portfolios, which is consistent with some of the results in Lettau, Maggiori, and Weber (2014) and Koijen et al. (2018). However, the downside risk beta is not significant for the CDP factor which also has a highly significant alpha. These results indicate that despite the fact of the CDP being a downside risk premium measure, the CDP factor cannot be explained by the equity market downside risk. Taken together, our results cannot be explained by, and are not subsumed by, a variety of well-established factors and risks in both commodity and equity markets.

4.3 Can CDP factor explain other factors?

As shown above that the CDP portfolio's returns are not spanned by existing factors, we now turn the tables and ask how much of the existing factors can be explained by the CDP factor. This is presented in the right panel of Table 4, where we report time-series regressions of various existing factors on the CDP factor returns.

The first column shows the factors under consideration. The column labeled "Mean" reports the mean of the factor returns over the 2001 to 2021 period. The remaining three columns report the regression intercept (Alpha), the loading on the CDP factor (Beta), and the regression R^2. We first examine the commodity-related factors. They are Basis H-L returns, Basis High portfolio returns, Basis Low portfolio returns, Momentum H-L returns, Commodity Market returns, and Carry returns of Koijen et al. (2018). The results are reported in the first six rows. Among the six commodity-related factors, only the Carry has a significant mean value of 56 basis points per month in our sample, but this drops to a statistically insignificant 22 basis points when we account for comovement the CDP factor. The regression R^2 for the Carry is as high as 16%, indicating our CDP factor does a good job explaining the Carry returns. Although the mean values of other commodity-related factors are statistically insignificant, they all load on the CDP factor significantly, as shown by the significant beta coefficients in the column labeled "Beta". The R^2's are also as high as 20% and 11% for the Basis and Basis High, respectively, again confirming the strong explanatory power of the CDP factor on Basis/Carry premiums. Given the theoretical connection between the CDP and Basis revealed in Section 2.3, and that the CDP amounts to a better risk premium measure than Basis, the results observed here are somewhat expected.

Next, we examine the equity market-related factors. Here we consider the Fama-French five factors individually. They are FF5F-mkt (market factor, the excess return on the equity market), FF5F-smb (size factor, the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios), FF5F-hml (value factor, the average return on the two value portfolios minus the average return on the two growth portfolios), FF5F-rmw (Robust Minus Weak factor, the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios), and FF5F-cma (Conservative Minus Aggressive, the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios). Although the R^2's are lower for the equity factors in general, the CDP factor still manages to bring the mean values of FF5F-mkt and FF5F-smb from significant 65 basis points and 30 basis points down to insignificant 48 basis points and 22 basis points, respectively. It is worth mentioning that FF5F-mkt load highly significantly on the CDP factor with a beta coefficient of 0.2. Considering the fact that the construction of CDP does not use any equity market information directly, this explanatory power on the equity market factor, FF5F-mkt, is impressive. The CDP factor does less well at explaining the other three FF5F factors, as reflected in lower R^2's, although FF5F-rmw and FF5F-cma still load significantly and negatively on the CDP factor.

In sum, as expected the CDP factor can explain the Basis/Carry factors of the commodity market well. We also find that the CDP factor does a good job explaining equity factors, especially the equity market factor, FF5F-mkt. This points to an interesting interaction between CDPs and the equity market returns, which we explore in more detail from a different perspective in the next section.

5 Predicting stock market returns using CDPs

In previous sections, we show the CDPs are characteristics that explain the cross-sectional commodity returns. In this section, we show that they also have predictive power going beyond the commodity markets and can be used to forecast the future stock market returns. The last two decades have witnessed extensive financialization of commodities in which institutional investors enter commodity futures markets. As a result of this prevailing financialization, theoretical studies (see Basak and Pavlova, 2016; Goldstein and Yang, 2021) predict strong co-movement of commodity and stock markets. However, the existing evidence on the predictive power of *commodity returns* on stock index returns has been underwhelming and mixed (see, e.g., Huang, Masulis, and Stoll, 1996; Black et al., 2014; Jacobsen, Marshall, and Visaltanachoti, 2019). The strong evidence of the CDP's predictive power on the stock market returns suggests that through the lens of the term structure model more forward looking information than the commodity returns per se can be extracted for effective prediction.

5.1 Aggregation techniques

In an attempt to construct aggregate predictors useful for forecasting, we use the Partial Least Square (PLS) (PLS, see, e.g., Kelly and Pruitt, 2013, 2015) to collectively and efficiently construct aggregate predictors from the individual commodity characteristics ($\text{CDP}_{i,t}$, i=1,...,N) by eliminating the negative effects of irrelevant to forecasting terms based on the future stock market excess returns. Further, we use a recently developed aggregation method named sPCA of Huang et al. (2022).[8] We also consider combination strategies between CDP_t^{PLS} and CDP_t^{sPCA}, to produce $\text{CDP}_t^{PLS+sPCA}$. For the in-sample analysis, we take the simple (average) combination of the aggregate PLS and sPCA predictors. However, in out-of-sample predictions, we use a simple but intuitive shifting strategy between PLS and sPCA, i.e., by using either CDP_t^{PLS} or CDP_t^{sPCA}, to forecast the excess stock market return at $t+h$ based on their past out-of-sample forecasting performance (at $t+h-1$), where h is the prediction horizon. In other words, we set $\text{CDP}_t^{PLS+sPCA}$ equal to CDP_t^{PLS} (CDP_t^{sPCA}) for forecasting the market at $t+h$ if the absolute forecast error is less by using CDP_{t-1}^{PLS} (CDP_{t-1}^{sPCA}) in comparison to CDP_{t-1}^{sPCA} (CDP_{t-1}^{PLS}) for predicting the market at

[8] Full technical details about the PLS and sPCA methods are provided in the Supplementary (Online) Appendix.

$t + h - 1$. Further, Table 6 provides the pairwise correlations among the 24 individual commodity characteristics used in this section.[9] The correlation coefficients range from -0.69 to 0.90, suggesting that the 24 commodity characteristics capture both common and different aspects. Hence, aggregate CDP predictors are necessary since using only individual commodity characteristics is unlikely to be complete in terms of the aggregate effect for forecasting the stock market.

[*Insert Table 6 about here*]

5.2 In-sample analysis and comparison with economic variables

We first run the following univariate predictive regression:

$$R_{t+1} = \alpha + \beta X_t + \epsilon_{t+1}, \tag{5.1}$$

where the stock market excess return at $t+1$ (R_{t+1}) is defined as the difference between the value-weight return of all CRSP firms in the US and the one-month T-bill rate. X_t is either one of the 14 economic variables in Welch and Goyal (2008), the investor sentiment index of Huang et al. (2015) denoted as S (available up to Dec 2020), the short interest index of Rapach, Ringgenberg, and Zhou (2016) denoted as SII, aggregate predictors extracted from the 14 economic variables by using PLS ($ECON^{PLS}$), sPCA ($ECON^{sPCA}$), and PLS+sPCA ($ECON^{PLS+sPCA}$), or aggregate CDP predictors constructed with PLS (CDP^{PLS}), sPCA (CDP^{sPCA}), and PLS+sPCA (CDP$^{PLS+sPCA}$).

The in-sample forecasting ability of X_t is tested by estimating regression Equation (5.1) over the entire sample period (February 1994 to March 2021). The null hypothesis is that X_t has no predictive power ($\hat{\beta} = 0$) and in this case, regression equation equation (5.1) reduces to $R_{t+1} = \alpha + \varepsilon_t$. The alternative hypothesis is that β is different from zero, and hence X_t contains useful information for predicting R_{t+1}. We use the Newey and West (1987) standard error to compute the t-statistic for $\hat{\beta}$.

[9] We use 24 (out of the 29 in Table 1) individual CDPs with full data history over the entire sample period (February 1994 to March 2021) Full history of data is necessary for the estimation of the various aggregation methods.

Panel A of Table 7 shows that out of the 14 economic predictors, only the dividend yield ratio (dy) displays significant positive predictive power for the market return at the 10% significance level. The in-sample R^2 of dy is larger than 1% as is the case for the dividend price ratio (dp) (1.55% for dp and 1.83% for dy). All the three aggregate CDP predictors CDP^{PLS}, CDP^{sPCA}, and $\text{CDP}^{PLS+sPCA}$ have positive statistical significant slopes at 1%, and their in-sample R^2's are 4.30%, 3.06%, and 3.78%, respectively, which are greater than the corresponding R^2's generated by the aggregate predictors extracted from the 14 economic variables ($ECON^{PLS}$, $ECON^{sPCA}$, and $ECON^{PLS+sPCA}$). Hence, CDP^{PLS}, CDP^{sPCA}, and $\text{CDP}^{PLS+sPCA}$ outperform the 14 economic predictors, the short interest and sentiment indices, as well as the three corresponding aggregate predictors extracted from economic variables in forecasting the excess stock market returns in-sample.

[*Insert Table 7 about here*]

We then investigate whether the predictive power of CDP^{PLS}, CDP^{sPCA} and $\text{CDP}^{PLS+sPCA}$ remains significant after controlling for a series of predictors. We conduct the following bivariate predictive regressions:

$$R_{t+1} = \alpha + \beta \text{CDP}_t^{PLS/sPCA/PLS+sPCA} + \psi Z_t^{\kappa} + \varepsilon_{t+1},\ \kappa = 1, \ldots, 17 \tag{5.2}$$

where Z_t^{κ} is one of the 14 individual economic predictors, the sentiment index, the short interest index, or an aggregate predictor extracted from economic variables constructed by using PLS, sPCA, and PLS+sPCA. Panel B of Table 7 shows that the estimates of the regression slopes of CDP_t^{PLS} remain statistically significant after controlling for each of the individual economic variables, the sentiment index, the short interest index, or $ECON^{PLS}$, suggesting that economic fundamentals fail to explain the impact of CDP^{PLS} on forecasting the excess stock market returns. Further, the magnitude of the β estimates of CDP^{PLS} is quite large since they are greater than 0.70% in all cases, while all of the in-sample R^2's in equation (5.2) are greater than 4.30% and substantially larger than those in equation (5.1), pointing out the economic significance of CDP^{PLS}. Similarly to CDP^{PLS}, CDP^{sPCA} and $\text{CDP}^{PLS+sPCA}$ also reach the same conclusions as shown in Panel C and D of Table 7.

Overall, Table 7 shows that the aggregate CDP has strong predictive power for the excess stock market returns in-sample beyond a wide variety of popular predictors.[10]

5.2.1 Controlling for uncertainty variables

In this section, we test whether a wide range of uncertainty measures can digest the in-sample forecasting power of CDP^{PLS}, CDP^{sPCA}, and CDP$^{PLS+sPCA}$. Specifically, we employ the financial uncertainty (FU) and macroeconomic uncertainty (MacroU) measures of Jurado, Ludvigson, and Ng (2015), the economic policy uncertainty measure (EPU) of Baker, Bloom, and Davis (2016), the uncertainty measure (UBEX) of Bekaert, Engstrom, and Xu (2014), as well as the "model-free" implied variance (IV), the "model-free" realized variance (RV), the variance risk premium (VRP), the expected variance risk premium (EVRP), and the expected realized variance (ERV) of Bollerslev, Tauchen, and Zhou (2009). Table 8 reports the results of forecasting the excess market returns with CDP^{PLS} (Panel A), CDP^{sPCA} (Panel B), and CDP$^{PLS+sPCA}$ (Panel C), after controlling for one of the uncertainty variables. We observe that the estimates of the regression slopes of the three CDP aggregate predictors remain statistically significant at the 1% level in all but one case, while their magnitude is quite large since they are greater than 0.70% in all cases.

[*Insert Table 8 about here*]

5.2.2 Pre- and post-financialization

In this section, we split the total sample into two periods, i.e., pre-financialization (Feb 1994- Dec 2000) and post-financialization (Jan 2001-Mar 2021) of commodities, to examine whether the aggregate CDP predictors generate a better performance during the post-financialization period. Table 8 reports the results of a univariate predictive regression for predicting the market excess returns with CDP^{PLS}, CDP^{sPCA}, and CDP$^{PLS+sPCA}$ over the pre- and post-financialization period in Panels A and B, respectively. We observe that the magnitude of the regression slopes of the three aggregate CDP predictors over the post-

[10] Our aggregate CDP indices can also predict cross-sectional stock returns sorted by industry, size, and value. The results are reported in the Supplementary (Online) Appendix

financialization period is greater than in the pre-financialization period. Further, the R^2's generated by CDP^{PLS}, CDP^{sPCA}, and CDP$^{PLS+sPCA}$ over the post-financialization period are 6.45%, 5.10% and 6.01%, respectively, which are greater than the corresponding R^2's generated over the pre-financialization period.

[*Insert Table 9 about here*]

5.3 Out-of-sample analysis

Although an in-sample analysis provides more efficient estimates and precise forecasts by exploiting the entire sample period, Welch and Goyal (2008), among many others, argue that out-of-sample forecasting evaluations are more relevant in practice. We start with an initial estimation window to generate the first out-of-sample forecast return as follows:

$$\hat{R}_{t+h} = \hat{\alpha} + \hat{\beta} X_t \tag{5.3}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are the OLS estimates of the predictive regression: $R_{t+h} = \alpha + \beta X_t + \epsilon_{t+h}$, where R_{t+h} is the average stock market excess return over the prediction horizon h. We then use an expanding estimation window approach and recursive predictive regressions to generate the out-of-sample forecasts for the following periods until the end of the sample period.

We evaluate the out-of-sample forecasting performance by using the R^2_{OS} statistic of Campbell and Thompson (2008) that measures the proportional reduction in mean squared forecast error (MSFE) for the predictive regression relative to the historical average. The out-of-sample analysis is based on a 20-year expanding estimation window. This is in line with Rapach, Strauss, and Zhou (2010), Huang et al. (2015) and Chen et al. (2022), among others, who also use a relatively long initial estimation window so that the various parameters in the aggregation techniques used in this section are estimated with more precision. In addition, we use the Clark and West (2007)'s MSFE-adjusted statistic for testing the hypothesis $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$ to uncover whether the predictive forecasts generate a statistically significant improvement in MSFE.

Table 10 presents the out-of-sample forecasting results for forecasting the average excess stock market returns over various prediction horizons by using aggregate predictors constructed with PLS (CDP^{PLS} & $ECON^{PLS}$) - Panel A, sPCA (CDP^{sPCA} & $ECON^{sPCA}$) - Panel B, and the dynamic shifting strategy between PLS and sPCA (CDP$^{PLS+sPCA}$ & $ECON^{PLS+sPCA}$) - Panel C. We find that all the three CDP aggregate predictors generate economically sizable R^2_{OS}'s across prediction horizons (up to two years, i.e., h= 24). For example, the R^2_{OS} of CDP^{PLS} equals 1.07% at the monthly horizon, and increases to over 5% for prediction horizons of six months and above (h $\geq$ 6). More importantly, the R^2_{OS}'s of CDP^{PLS} are statistically significant across prediction horizons according to the MSFE-adjusted statistics, meaning that the out-of-sample MSFEs generated by CDP^{PLS} are significantly lower than that of the historical means. Similarly to CDP^{PLS}, CDP^{sPCA} and CDP$^{PLS+sPCA}$ also generate statistically significant R^2_{OS}'s in most of the prediction horizons we examine. In contrast, $ECON^{PLS}$, $ECON^{sPCA}$ and $ECON^{PLS+sPCA}$ generate negative R^2_{OS}'s, except for $ECON^{PLS+sPCA}$ at prediction horizons of 18 months and above. Since a monthly out-of-sample R^2_{OS} of 0.5% can generate substantial economic value (Campbell and Thompson, 2008), in the following section we also conduct an asset allocation analysis to examine potential gains for mean-variance investors by using CDP^{PLS}, CDP^{sPCA} and CDP$^{PLS+sPCA}$.

[*Insert Table 10 about here*]

5.4 Economic value of predicting stock index

This section evaluates the economic value of forecasting stock market returns with the aggregate CDP predictors from the portfolio management perspective. Following Kandel and Stambaugh (1996), Campbell and Thompson (2008), Ferreira and Santa-Clara (2011), Huang et al. (2015), Jiang et al. (2019), Chen et al. (2022), among others, we use the certainty equivalent return (CER), which can be interpreted as the risk-free return that an investor would trade for a higher return associated with a given risk, as well as the Sharpe ratio.

Suppose a mean-variance investor allocates his wealth between the stock market and the risk-free asset. Assume that he is maximizing the next one-month expected utility by investing a proportion of w_t to the stock market and a proportion of $1 - w_t$ to the risk-free asset at the start of each month:

$$U(R_{p,t+1}) = \mathbb{E}(R_{p,t+1}) - \frac{\lambda}{2}\mathbb{V}ar(R_{p,t+1}), \tag{5.4}$$

where $\mathbb{E}(R_{p,t+1})$ and $\mathbb{V}ar(R_{p,t+1})$ denote the mean and variance of the excess portfolio returns at $t+1$, respectively, and λ is the investor's risk aversion. The investor's portfolio return at the end of each month $(t+1)$ is given by:

$$R_{p,t+1} = w_t R_{t+1} + R_{f,t+1}, \tag{5.5}$$

where R_{t+1} and $R_{f,t+1}$ are the excess stock market return and the risk-free rate, respectively, at $t+1$. With some simple algebra, one can easily compute the optimal portfolio weight to the stock market (w_t) at time t as follows:

$$w_t = \frac{1}{\lambda}\frac{\hat{R}_{t+1}}{\hat{\sigma}^2_{t+1}}, \tag{5.6}$$

where the mean $(\hat{R}_{t+1})$ and variance $(\hat{\sigma}^2_{t+1})$ estimates of the market excess returns at $t+1$ used for computing w_t in Equation (5.6) are estimated based on information up to time t. We use a 60 month rolling window for estimating the variance of market excess returns, and follow Campbell and Thompson (2008) by ruling out short selling and allowing at most 50% leverage such that $0 \leq w_t \leq 1.5$.

The CER of a portfolio is:

$$CER = \hat{\mu}_p - 0.5\lambda\hat{\sigma}^2_p, \tag{5.7}$$

where $\hat{\mu}_p$ and $\hat{\sigma}^2_p$ are the mean and variance of portfolio excess returns over the entire out-of-sample period. The difference between the CERs (and SRs) by using each of the aggregate

CDP predictors and the historical means is a measure of the predictability's economic value.

Table 11 reports the asset allocation results of a mean-variance investor, with a risk aversion coefficient of five,[11] by using aggregate predictors constructed with PLS (CDP^{PLS} & $ECON^{PLS}$) - Panel A, sPCA (CDP^{sPCA} & $ECON^{sPCA}$) - Panel B, and PLS+sPCA (CDP$^{PLS+sPCA}$ & $ECON^{PLS+sPCA}$) - Panel C, for predicting future market excess returns relative to historical mean returns. Further, we consider three cases: zero transaction cost, as well as proportional transaction costs of 25 and 50 basis points (bps) per transaction. We observe that the three aggregate CDP predictors generate economically sizable investment profits, except for CDP^{sPCA} when considering proportional transaction costs of 50 bps. When there is no transaction cost, the annualized CER gain of CDP^{PLS} is 1.50% at the monthly horizon, implying that an investor would be willing to pay an annual fee of up to 150 bps to access the predictive forecasts of CDP^{PLS}. These large investment gains also maintain when considering transaction costs. Similarly to CDP^{PLS}, CDP^{sPCA} and CDP$^{PLS+sPCA}$ also generate substantial economic values in asset allocation. In contrast, aggregate predictors extracted from economic variables generate negative CER gains, except for $ECON^{PLS}$ when considering zero and 25 bps proportional transaction costs.

[*Insert Table 11 about here*]

Furthermore, investment portfolios based on aggregate CDP predictors generate large Sharpe ratios. When there is no transaction cost, as Table 11 shows, the annualized Sharpe ratios for CDP^{PLS}, CDP^{sPCA} and CDP$^{PLS+sPCA}$ are 0.88, 0.82 and 0.88, respectively, and outperform the corresponding aggregate predictors constructed with economic variables. After deducting for 25 (50) bps transaction cost, they are 0.86 (0.84), 0.80 (0.78) and 0.85 (0.82). Overall, there are potentially large economic gains in the asset allocation based on aggregate CDP predictors, suggesting substantial economic values for mean-variance investors. Hence, this analysis emphasizes their crucial role on the stock market from an investment management perspective.

[11] Our results are robust to alternative reasonable risk aversion coefficient values, and are reported in the Supplementary (Online) Appendix.

In summary, there are potentially large economic gains in the asset allocation based on aggregate CDP predictors, suggesting substantial economic values for mean-variance investors. This analysis then emphasizes the crucial role of aggregate CDP predictors constructed on the stock market from an investment management perspective.

5.5 Out-of-sample analysis with alternative methods

In the previous sections, we have shown that market returns can be significantly predicted by CDP^{PLS}, CDP^{sPCA} and $\text{CDP}^{PLS+sPCA}$. We now examine whether our conclusions are robust to alternative econometric and machine learning methods. Particularly, we consider the combination ENet (C-ENet) of Dong et al. (2022), the simple (average) combination forecast of the individual univariate forecasts (Ave), and the Ridge shrinkage regression of Hoerl and Kennard (1970).

[*Insert Table 12 about here*]

Table 12 presents the out-of-sample results. There are many observations. First, all three alternative methods generate economically sizable out-of-sample R^2_{OS}'s across prediction horizons (up to two years, i.e., h=24). Second, all the R^2_{OS}'s generated by C-ENet and Ridge are statistically significant across prediction horizons according to the MSFE-adjusted statistics. Finally, while these three alternative methods work well for predicting market returns, they generally underperform the PLS method, especially for longer prediction horizons. This finding is in accordance with Kelly and Pruitt (2015)'s conclusion, e.g., the PLS forecast is asymptotically consistent and generates the minimum MSFE as long as the consistency condition is satisfied.

5.6 Why CDP predicts stock index returns?

In this section, we take a closer look at why the CDP indices predict stock index returns. According to Cochrane (2011), if a variable can predict market returns it must predict cash flow news or/and discount rate news. Therefore, in the first part of the section, we investigate if the CDP indices' predictability comes from the discount rate channel or cash flow channel. We use the VAR framework developed by Campbell (1991) and extended by Campbell and Ammer (1993) to measure the news components. We analyze the source of predictability by studying the CDP indices' ability to forecast these components constituting the total stock returns. In the second part of the section, we study whether the CDP indices can forecast changes in economic activities to shed further light on the interlinkages between stock markets and commodity markets. Given that the commodity usually serves as a hedge against inflation fluctuations, we study the impact of the CDP indices on inflation rates.

5.6.1 Discount rate or cash flow channel

We start with a predictive regression by regressing the stock returns on the CDP indices. We examine all three CDP indices, i.e., CDP^{PLS}, CDP^{sPCA} and $\text{CDP}^{PLS+sPCA}$,

$$R_{t+1} = \alpha + \beta \ \text{CDP}_t^k + \epsilon_{t+1}, \quad k = PLS, sPCA, PLS + sPCA \tag{5.8}$$

According to Campbell (1991), the stock returns can be decomposed into three different components,

$$R_{t+1} = E_t(R_{t+1}) + \eta_{t+1}^{CF} - \eta_{t+1}^{DR}, \tag{5.9}$$

where $E_t(R_{t+1})$ is the expected stock index return, η_{t+1}^{CF} and η_{t+1}^{DR} are the cash flow news and discount news components, respectively. Following Cochrane (2011), we perform the following predictive regressions for the estimates of each component of stock returns on the right-hand side of Eq. (5.9),

$$E_t(R_{t+1}) = \alpha + \beta_E \ \text{CDP}_t^k + \epsilon_{t+1}^E, \tag{5.10}$$

$$\eta_{t+1}^{CF} = \beta_{CF} \ \text{CDP}_t^k + \epsilon_{t+1}^{CF}, \tag{5.11}$$

$$\eta_{t+1}^{DR} = \beta_{DR} \ \text{CDP}_t^k + \epsilon_{t+1}^{DR}, \tag{5.12}$$

where $k = PLS, sPCA, PLS + sPCA$. The properties of OLS imply that:

$$\beta = \beta_E + \beta_{CF} - \beta_{DR}, \tag{5.13}$$

By comparing the estimated coefficients in Eq. (5.8) and in Eqs. (5.10) through (5.12), we can ascertain the extent to which the CDP indices' ability to predict the stock index returns relates to its ability to forecast the three components specified on the right-hand side of Eq. (5.9). We estimate the expected stock returns, cash flow news, and discount rate news components using individual VARs comprising the log stock index return, log dividend-price ratio, and one of the 14 macroeconomic variables explored in Welch and Goyal (2008). According to Engsted, Pedersen, and Tanggaard (2012), it is important to include the log dividend-price ratio to properly estimate the cash flow news and the discount rate news components. We have also done an alternative regression based on a VAR of the log stock index return, log dividend-price ratio, and the first three principal components based on the 14 macroeconomic variables of Welch and Goyal (2008). The sample period is from February 1994 to March 2021.

[*Insert Table 13 about here*]

In Table 13, we present the results of predictive estimates of β_E, β_{CF}, and β_{DR} in Eqs. (5.10) through (5.12). We also report β of the OLS predictive regression specified in Eq. (5.8). The second last row is the result of the return decomposition based on the VAR comprised of the log stock return, log dividend-price ratio, and the first three principal components of 14 macroeconomic variables of Welch and Goyal (2008).

The relation given by Eq.(5.13) holds for the estimates of β and each set of β_E, β_{CF}, and β_{DR} estimates for each CDP index, CDP^{PLS}, CDP^{sPCA} and CDP$^{PLS+sPCA}$. For example, when the VAR is based on the log stock return and the log dividend-price ratio, the regression slope is 0.31, 0.25 and 0.29 on the expected return, 0.41, 0.39 and 0.40 on the cash flow news and -0.24, -0.18 and -0.21 on the discount rate news for CDP^{PLS}, CDP^{sPCA} and CDP$^{PLS+sPCA}$, respectively. The sum of the three slopes on the right hand side of Eq.(5.13) is 0.31+0.41+0.24=0.96, 0.25+0.39+0.18=0.82 and 0.29+0.40+0.21=0.90 for

CDP^{PLS}, CDP^{sPCA} and CDP$^{PLS+sPCA}$, respectively, which exactly equals to the estimate of β when the log stock return is the dependent variable in Eq. (5.9) reported in the last row.

All of the β_E and β_{CF} estimates are highly significant, however, the β_{CF} estimates are typically much larger in magnitude than the β_E, indicating that both expected returns and cash flow affect the stock returns but with the cash flow as the dominant channel transferring the impact of CDP index. In contrast, most of the β_{DR} are insignificant (besides the results using the log stock return, log dividend-price ratio, and the 3-month treasury bill rate at a 10% significance level). The results indicate that the most economically important source of predictability comes from anticipating cash flow news. The result is supported by the theoretical studies of Basak and Pavlova (2016) and Goldstein and Yang (2021) who show that the large flow of capital makes the financial market and commodity market more integrated.[12] Overall, the results in Table 13 indicate that the CDP indices contain substantially different information from that found in other existing return predictors, and the differential information in the CDP indices is particularly relevant for future cash flows.

5.6.2 The predictability of CDP indices on real economy variables

In this section, we consider whether the CDP indices can forecast changes in economic activities. We study the predictability of the CDP indices on one of the most important economic indicators, inflation. The relevant question is whether the CDP indices have predictive power beyond the past inflation values. We estimate an ARMA model as follows,

$$y_t = \alpha + \beta \varDelta \mathrm{CDP}^k_{t-3} + \theta_1 y_{t-1} + \theta_2 \epsilon_{t-1} + \epsilon_t, \quad k = PLS, sPCA, PLS + sPCA. \tag{5.14}$$

where y_t is the difference in consumer price inflation (CPI) for all urban consumers at $t+1$ and t, i.e., $y_t = \mathrm{CPI}_{t+1} - \mathrm{CPI}_t$. Following Bakshi, Panayotov, and Skoulakis (2011), we calculate the shocks to the CDP indices as the difference between index values at t and $t-3$, denoted as $\varDelta \mathrm{CDP}^k_{t-3}$. k denotes the different aggregation methods, i.e., PLS, $sPCA$, and

[12]Our result is also consistent with Rapach, Ringgenberg, and Zhou (2016) who identify that the short-term interest rates affect the stock return mainly through the cash flow channel.

$PLS + sPCA$. Four model specifications are considered: inflation-only and inflation with one of the three CDP indices (one of CDP^{PLS}, CDP^{sPCA}, and CDP$^{PLS+sPCA}$). The results are reported in Table 14.

From Table 14, we note that both AR and MA are highly positively significant and the shocks to the CDP index are negatively related to the subsequent changes in inflation and the effects are highly statistically significant. Meanwhile, adding a CDP index to the model significantly improves the model's goodness of fit to the data. For example, the AIC decreases from the inflation-only's -2840 to -2842, -2845 and -2845 for the models with CDP^{PLS}, CDP^{sPCA}, and CDP$^{PLS+sPCA}$, respectively; the log-likelihood ($logL$) function increases from 1424 to 1426, 1427 and 1428, respectively.

In general, our CDP indices provide incremental predictive power to inflation beyond its past data. These results complement the evidence on the predictive links between the real economy and the commodity markets (see, e.g., Bakshi, Panayotov, and Skoulakis, 2011; Cespedes and Velasco, 2012; Caballero and Gourinchas, 2012, etc.) and also testify the predictability of the CDPs on stock returns.

[*Insert Table 14 about here*]

6 Conclusion

Building on the term structure modeling and option pricing literature, we develop a term structure model-based measure of commodity downside risk premium for individual commodities. This captures the information from spot, futures and option markets on the downside risk implied by the model. We find that this risk measure has strong explanatory power for the cross-section of commodity returns. None of the well-known commodity market and equity market factors are able to explain the returns of the H-L portfolio constructed from sorting by our measure. The returns also do not load on the market downside risk. Our risk measure not only explains the cross-section of commodity returns but also predicts the stock market returns. In our predictive analysis, we show that aggregate commodity risk indices constructed from the individual risk measure using the PLS, sPCA, and a combination of them have significant predictive power for the stock market returns that goes beyond the information of other typical economic predictors.

Our results point to new directions for future research in the commodity market. Accurate measures of downside risk premium in individual commodities seem to be rather heterogeneous. It remains an open question whether the heterogeneity is due to financial market structure or industrial/production structure. We have shown that the term structure modeling has proven fruitful in commodity markets' cross-sectional asset pricing and predicting stock market returns. But the implication to other markets, such as corporate bonds and currencies, are unknown. These are interesting issues that demands substantial new research.

References

Babbs, Simon H and K Ben Nowman (1999). "Kalman filtering of generalized Vasicek term structure models". In: *Journal of financial and quantitative analysis* 34.1, pp. 115–130.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis (2016). "Measuring Economic Policy Uncertainty". In: *The Quarterly Journal of Economics* 131, pp. 1593–1636.

Bakshi, G., X. Gao, and A.G. Rossi (2019). "Understanding the sources of risk underlying the cross section of commodity returns". In: *Management Science* 65, pp. 619–641.

Bakshi, Gurdip, George Panayotov, and Georgios Skoulakis (2011). "The Baltic Dry Index as a Predictor of Global Stock Returns, Commodity Returns, and Global Economic Activity". In: *Working paper, University of Maryland.*

Basak, Suleyman and Anna Pavlova (2016). "A model of financialization of commodities". In: *The Journal of Finance* 71.4, pp. 1511–1556.

Bekaert, Geert, Eric C. Engstrom, and Nancy R. Xu (2014). "The Time Variation in Risk Appetite and Uncertainty". In: *Management Science* 68.6, pp. 3975–4004.

Bekaert, Geert and Marie Hoerova (2014). "The VIX, the variance premium and stock market volatility". In: *Journal of econometrics* 183.2, pp. 181–192.

Black, Angela J, Olga Klinkowska, David G McMillan, and Fiona J McMillan (2014). "Forecasting stock returns: do commodity prices help?" In: *Journal of Forecasting* 33.8, pp. 627–639.

Bollerslev, Tim, George Tauchen, and Hao Zhou (2009). "Expected stock returns and variance risk premia". In: *The Review of Financial Studies* 22.11, pp. 4463–4492.

Brennan, MJ (1991). "The price of convenience and the valuation of commodity contingent claims,[w:] D. Land, B. Oeksendal". In: *Stochastic Models and Options Values, Elsevier Science Publica-tions.*

Caballero, R. Farhi and E. Gourinchas (2012). "Financial crash, commodity prices and global imbalances". In: *NBER Working paper series* 14521.

Campbell, J. Y. (1991). "A variance decomposition for stock returns". In: *Economic Journal* 101, pp. 157–179.

Campbell, J. Y. and J. Ammer (1993). “What moves the stock and bond markets? A variance decomposition for long-term asset returns”. In: *Journal of Finance* 48, pp. 3–37.

Campbell, John Y and Samuel B Thompson (2008). “Predicting excess stock returns out of sample: Can anything beat the historical average?” In: *The Review of Financial Studies* 21.4, pp. 1509–1531.

Casassus, J. and P. Collin-Dufresne (2005). “Stochastic convenience yield implied from commodity futures and interest rates”. In: *The Journal of Finance* 60.5, pp. 2283–2331.

Cespedes, Luis Felipe and Andres Velasco (2012). “Macroeconomic Performance During Commodity Price Booms and Busts”. In: *IMF Economic Review* 60, pp. 570–500.

Chen, Jian, Guohao Tang, Jiaquan Yao, and Guofu Zhou (2022). “Investor attention and stock returns”. In: *Journal of Financial and Quantitative Analysis* 57.2, pp. 455–484.

Cheng, Ing-Haw (2019). “The VIX premium”. In: *The Review of Financial Studies* 32.1, pp. 180–227.

Cheng, Ing-Haw. and Wei Xiong (2014). “The financialization of commodity markets”. In: *Annual Review of Financial Economics* 6, pp. 419–441.

Chiang, I-HSUAN ETHAN, W Keener Hughen, and Jacob S Sagi (2015). “Estimating oil risk factors using information from equity and derivatives markets”. In: *The Journal of Finance* 70.2, pp. 769–804.

Clark, Todd E and Kenneth D West (2007). “Approximately normal tests for equal predictive accuracy in nested models”. In: *Journal of econometrics* 138.1, pp. 291–311.

Cochrane, J. H. (2011). “Presidential address: Discount rates”. In: *Journal of Finance* 66.4, pp. 1047–1108.

Dai, Q. and K.J. Singleton (2000). “Specification analysis of affine term structure models”. In: *Journal of Finance* 55.5, pp. 1943–1978.

Daskalaki, Charoula, Alexandros Kostakis, and George Skiadopoulos (2014). “Are there common factors in individual commodity futures returns?” In: *Journal of Banking & Finance* 40, pp. 346–363.

De Jong, F. (2000). “Time series and cross-section information in affine term-structure models”. In: *Journal of Business & Economic Statistics* 18.3, pp. 300–314.

De Roon, F.A., T.E. Nijman, and C Veld (2000). “Hedging pressure effects in futures markets”. In: *Journal of Finance* 55, pp. 1437–1456.

Dong, Xi, Yan Li, David E Rapach, and Guofu Zhou (2022). “Anomalies and the expected market return”. In: *The Journal of Finance* 77.1, pp. 639–681.

Duffee, G.R. (2002). “Term premia and interest rate forecasts in affine models”. In: *Journal of Finance* 57, pp. 405–443.

Duffie, D., J. Pan, and K. Singleton (2000). “Transform analysis and asset pricing for affine jump-diffusions”. In: *Econometrica*, pp. 1343–1376.

Engsted, T., T. Q. Pedersen, and C. Tanggaard (2012). “Pitfalls in var based return decompositions: A clarification”. In: *Journal of Banking and Finance* 36, pp. 1255–1265.

Erb, C.B. and C.R. Harvey (2006). “The strategic and tactical value of commodity futures”. In: *Financial Analysts Journal* 62, pp. 69–97.

Fama, Eugene F and Kenneth R French (2015). “A five-factor asset pricing model”. In: *Journal of financial economics* 116.1, pp. 1–22.

Ferreira, Miguel A and Pedro Santa-Clara (2011). “Forecasting stock market returns: The sum of the parts is more than the whole”. In: *Journal of Financial Economics* 100.3, pp. 514–537.

Friedman, Nicole (Oct. 2014). “Why the Drop in Oil Prices Caught So Many by Surprise”. In: *The Wall Street Journal*.

Gibson, Rajna and Eduardo S Schwartz (1990). “Stochastic convenience yield and the pricing of oil contingent claims”. In: *The Journal of Finance* 45.3, pp. 959–976.

Goldstein, Itay and Liyan Yang (2021). “Commodity financialization and information transmission”. In: *Forthcoming the Journal of Finance.*

Gorton, Gary B, Fumio Hayashi, and K Geert Rouwenhorst (2013). “The fundamentals of commodity futures returns”. In: *Review of Finance* 17.1, pp. 35–105.

Hamilton, James Douglas (1994). *Time series analysis*. Princeton university press.

Harvey, Andrew C (1989). *Forecasting, structural time series models and the Kalman filter*. Cambridge university press.

Hoerl, A. and R. Kennard (1970). “Ridge Regression: Biased Estimation for Nonorthogonal Problems”. In: *Technometrics* 12, pp. 55–67.

Huang, Dashan, Fuwei Jiang, Kunpeng Li, Guoshi Tong, and Guofu Zhou (2022). “Scaled PCA: A New Approach to Dimension Reduction”. In: *Management Science* 68.3, pp. 1678–1695.

Huang, Dashan, Fuwei Jiang, Jun Tu, and Guofu Zhou (2015). “Investor sentiment aligned: A powerful predictor of stock returns”. In: *The Review of Financial Studies* 28.3, pp. 791–837.

Huang, Roger D, Ronald W Masulis, and Hans R Stoll (1996). “Energy shocks and financial markets”. In: *The Journal of Futures Markets (1986-1998)* 16.1, p. 1.

Jacobsen, Ben, Ben R Marshall, and Nuttawat Visaltanachoti (2019). “Stock market predictability and industrial metal returns”. In: *Management Science* 65.7, pp. 3026–3042.

Jiang, Fuwei, Joshua Lee, Xiumin Martin, and Guofu Zhou (2019). “Manager sentiment and stock returns”. In: *Journal of Financial Economics* 132.1, pp. 126–149.

Jurado, K., S. C. Ludvigson, and S Ng (2015). “Measuring uncertainty”. In: *American Economic Review* 105.3, pp. 1177–1216.

Kandel, Shmuel and Robert F Stambaugh (1996). “On the predictability of stock returns: an asset-allocation perspective”. In: *The Journal of Finance* 51.2, pp. 385–424.

Kelly, Bryan and Seth Pruitt (2013). “Market expectations in the cross-section of present values”. In: *The Journal of Finance* 68.5, pp. 1721–1756.

— (2015). “The three-pass regression filter: A new approach to forecasting using many predictors”. In: *Journal of Econometrics* 186.2, pp. 294–316.

Koijen, Ralph SJ, Tobias J Moskowitz, Lasse Heje Pedersen, and Evert B Vrugt (2018). “Carry”. In: *Journal of Financial Economics* 127.2, pp. 197–225.

Lettau, Martin, Matteo Maggiori, and Michael Weber (2014). “Conditional risk premia in currency markets and other asset classes”. In: *Journal of Financial Economics* 114.2, pp. 197–225.

Light, Nathaniel, Denys Maslov, and Oleg Rytchkov (2017). "Aggregation of information about the cross section of stock returns: A latent variable approach". In: *The Review of Financial Studies* 30.4, pp. 1339–1381.

Liu, Peng and Ke Tang (2011). "The stochastic behavior of commodity prices with heteroskedasticity in the convenience yield". In: *Journal of Empirical Finance* 18.2, pp. 211–224.

Newey, Whitney K and Kenneth D West (1987). "Hypothesis testing with efficient method of moments estimation". In: *International Economic Review*, pp. 777–787.

Rapach, D., M. Ringgenberg, and G. Zhou (2016). "Short interest and aggregate stock returns". In: *Journal of Financial Economics* 121.1, pp. 46–65.

Rapach, David E, Jack K Strauss, and Guofu Zhou (2010). "Out-of-sample equity premium prediction: Combination forecasts and links to the real economy". In: *The Review of Financial Studies* 23.2, pp. 821–862.

Rapach, David E. and Guofu Zhou (2022). "Asset Pricing: Time-Series Predictability". In: *Oxford Research Encyclopedia of Economics and Finance*.

Ross, Stephen A (1997). "Hedging long run commitments: Exercises in incomplete market pricing". In: *ECONOMIC NOTES-SIENA-*, pp. 385–420.

Schwartz, Eduardo and James E Smith (2000). "Short-term variations and long-term dynamics in commodity prices". In: *Management Science* 46.7, pp. 893–911.

Schwartz, Eduardo S (1997). "The stochastic behavior of commodity prices: Implications for valuation and hedging". In: *The Journal of finance* 52.3, pp. 923–973.

Szymanowska, Marta, Frans De Roon, Theo Nijman, and Rob Van Den Goorbergh (2014). "An anatomy of commodity futures risk premia". In: *The Journal of Finance* 69.1, pp. 453–482.

Trolle, A.B. and E.S. Schwartz (2009). "Unspanned stochastic volatility and the pricing of commodity derivatives". In: *Review of Financial Studies* 22.11, p. 4423.

Vasicek, O. (1977). "An equilibrium characterization of the term structure". In: *Journal of Financial Economics* 5.2, pp. 177–188.

Welch, Ivo and Amit Goyal (2008). "A comprehensive look at the empirical performance of equity premium prediction". In: *The Review of Financial Studies* 21.4, pp. 1455–1508.

Yang, Fan (2013). "Investment shocks and the commodity basis spread". In: *Journal of Financial Economics* 110.1, pp. 164–184.

Figure 1: Front month futures total return, January 2001 - March 2021

This figure plots the total returns of the front month futures of all 29 commodities from January 2001 to March 2021, with initial value set at 1. The solid line is the cross-sectional mean, the grey area is the cross-sectional 90 and 10 percentiles, repectively.

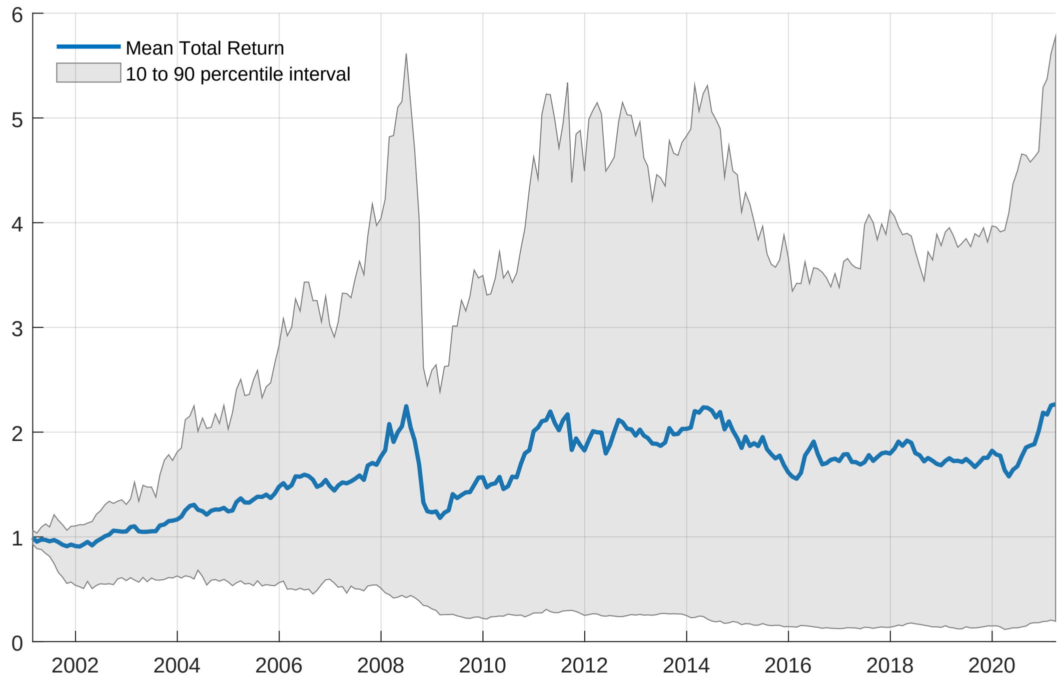

Figure 2: Cross-sectional risk premiums: January 2001 - March 2021

The five panels in this figure plot the cross-section CDPs from January 2001 to July 2020 for all types (All), Agriculture, Energy, Livestock, and Metals, respectively. The solid line is the cross-sectional mean, the grey area is the cross-sectional maximum and minimum.

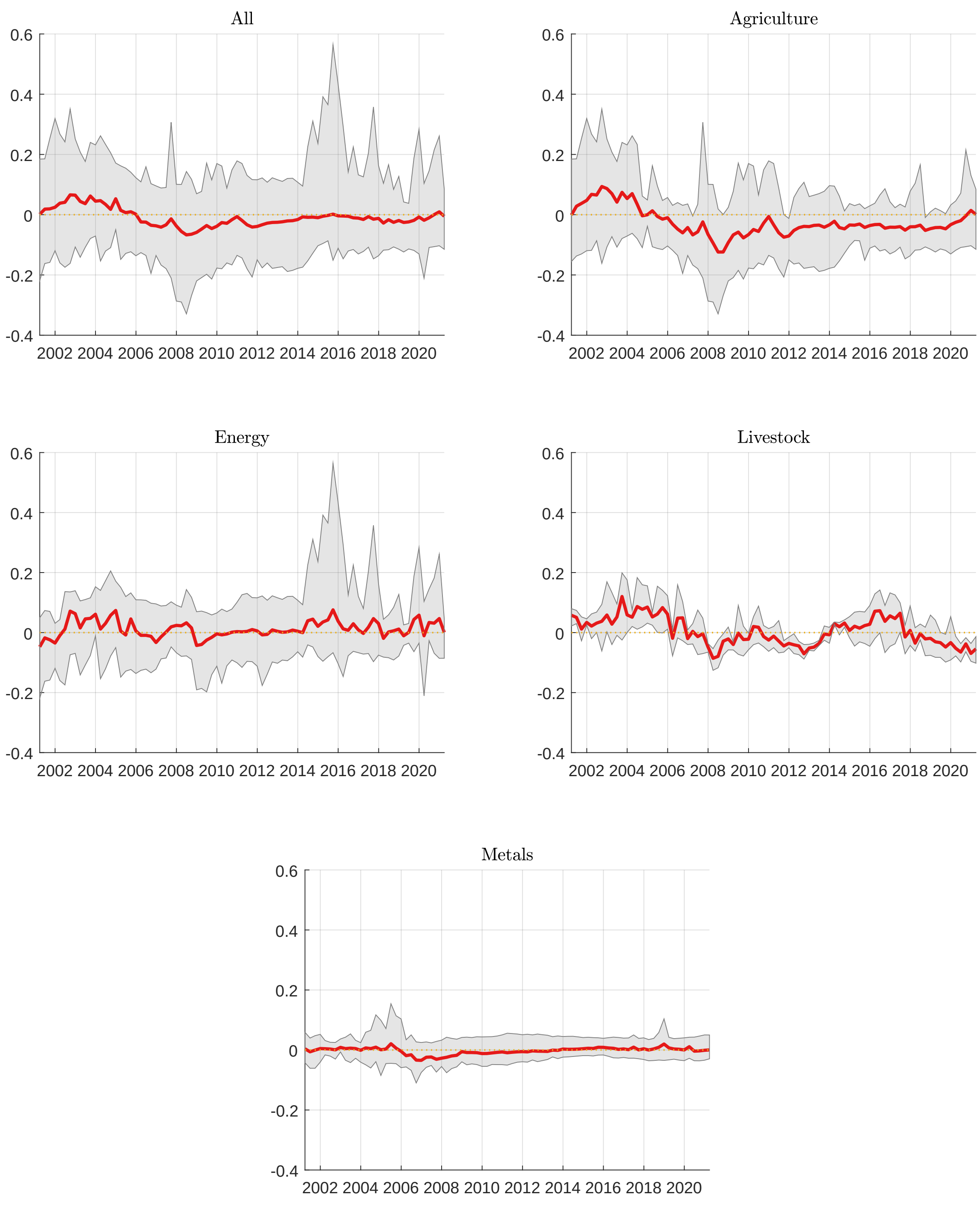

Figure 3: Cumulative returns of H-L Portfolios

This figure plots the cumulative returns of the high minus low portfolios sorted by the CDP (solid line), Basis (dashed line) and Momentum (dotted line), respectively. The sample period is January 2001 - March 2021.

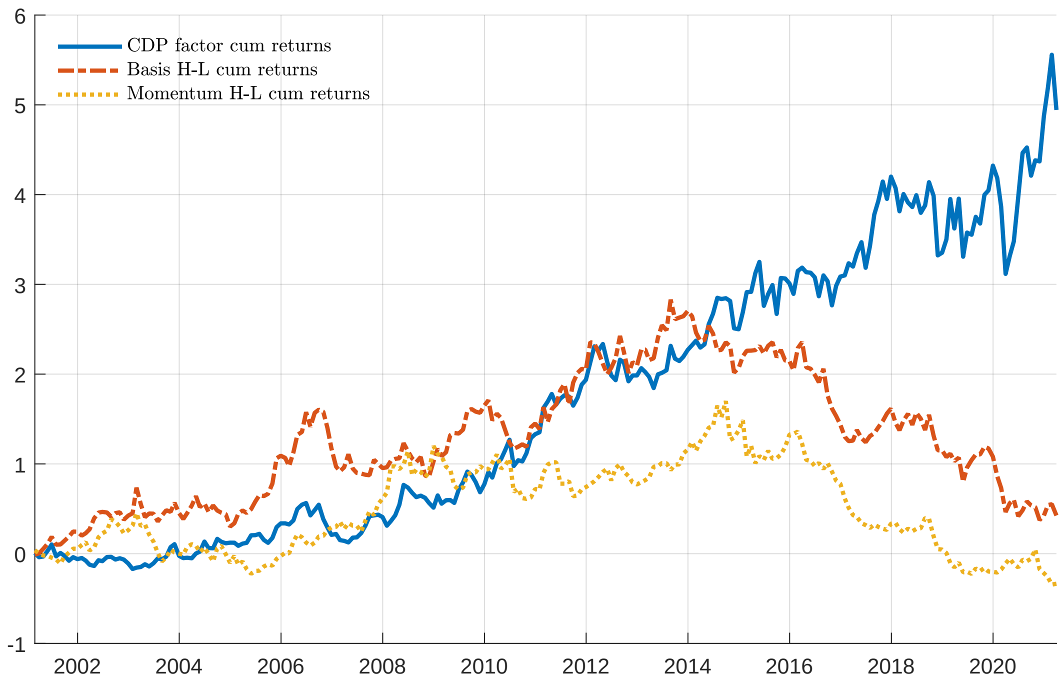

Figure 4: Total variations explained by PCs

This figure plots the total variations of CDPs explained by the first 10 PCs. The left Y-axis measures the explained percentage by individual PCs, and the right Y-axis measures the explained percentage cumulatively.

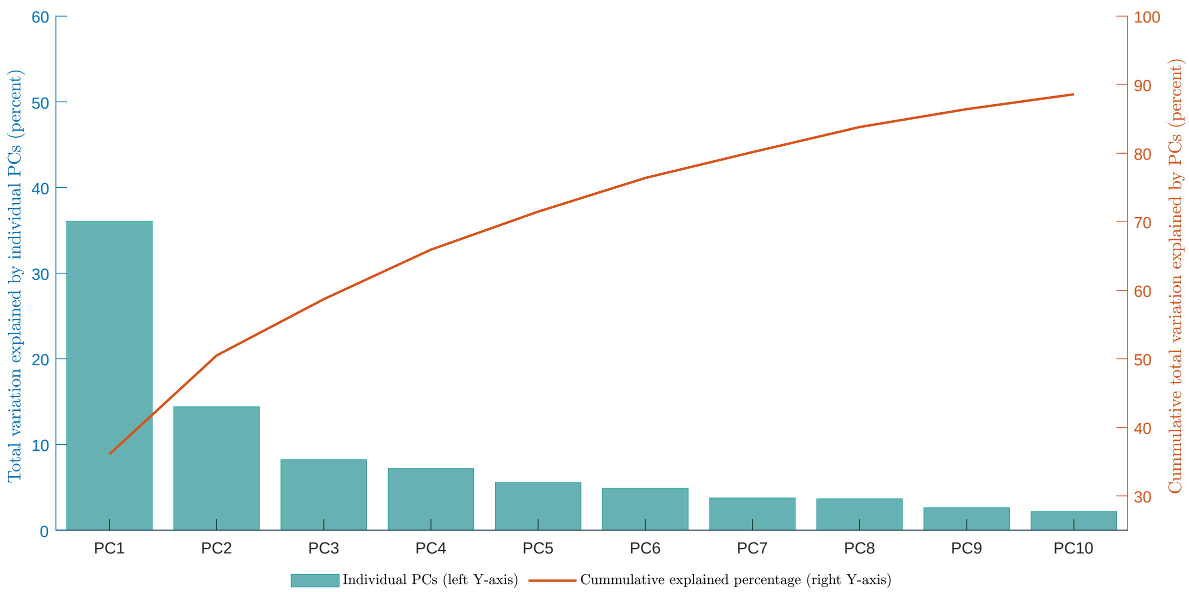

Table 1: Commodity names and summary statistics

The left three columns are the names, types, and Reuters Instrument Code (RIC) of all 29 commodity futures in four types (seven Energy commodities, 14 Agriculture commodities, three Livestock commodities, and five Metals commodities) included in our sample. The right five columns present the summary statistics of the monthly returns of the front month futures, the Mean, Standard deviation (Std), Minimum (Min), Median, and Maximum (Max). All numbers shown are in the raw value.

Commodity Type	Name	RIC	Mean	Std	Min	Median	Max
Energy	Crude oil	LCO	0.006	0.095	-0.469	0.013	0.337
	Heating oil	LHO	-0.001	0.089	-0.320	0.001	0.253
	Natural gas	NG	-0.020	0.133	-0.320	-0.021	0.516
	RBOB gasoline	RB	0.007	0.105	-0.599	0.013	0.335
	Propane	A7E	0.012	0.108	-0.256	0.026	0.302
	Natural gas (ICE)	NGLNQ	-0.011	0.102	-0.316	-0.016	0.450
	Gas oil	LGO	0.007	0.094	-0.334	0.009	0.271
Agriculture	Corn	C	-0.001	0.081	-0.228	-0.009	0.283
	Kansas wheat	KW	-0.001	0.086	-0.241	-0.008	0.360
	Oats	O	0.012	0.100	-0.267	0.005	0.350
	Soybean meal	SM	0.015	0.086	-0.272	0.009	0.301
	Soybean oil	BO	0.005	0.075	-0.252	0.002	0.269
	Soybeans	S	0.010	0.074	-0.234	0.009	0.196
	Wheat	W	-0.004	0.088	-0.252	-0.008	0.377
	Cocoa	CC	0.009	0.091	-0.250	0.008	0.332
	Coffee	KC	-0.002	0.091	-0.236	-0.011	0.436
	Cotton	CT	0.000	0.083	-0.226	0.004	0.247
	Sugar	SB	0.002	0.090	-0.297	-0.003	0.311
	Rough rice	RR	-0.003	0.075	-0.228	-0.001	0.222
	Orange juice	OJ	0.001	0.089	-0.210	-0.007	0.276
	Lumber	LB	0.004	0.110	-0.322	-0.009	0.584
Livestock	Feeder cattle	FC	0.002	0.046	-0.206	0.002	0.128
	Lean hogs	LH	-0.001	0.091	-0.260	-0.002	0.385
	Live cattle	LC	0.002	0.046	-0.231	0.003	0.160
Metals	Copper	HG	0.010	0.077	-0.360	0.007	0.354
	Gold	GC	0.007	0.048	-0.183	0.004	0.136
	Palladium	PA	0.018	0.081	-0.222	0.028	0.249
	Platinum	PL	-0.001	0.063	-0.181	-0.001	0.140
	Silver	SI	0.009	0.091	-0.280	0.003	0.301

Table 2: CDPs' factor loadings on the first five PCs

This table reports the cross-sectional averages and their standard deviations (in parentheses) of the factor loading coefficients, which are slopes from time series regressions of all 29 CDPs on the first five PCs. In the 'All' row, the loading coefficients for all 29 CDPs are included in the calculation, in other sector-specific rows, only loading coefficients for the CDPs in the corresponding sector are included in the calculation.

Sector	PC1	PC2	PC3	PC4	PC5
All	0.102	0.059	0.045	0.042	0.052
	(0.158)	(0.179)	(0.183)	(0.184)	(0.182)
Energy	0.005	-0.034	0.130	0.077	0.082
	(0.169)	(0.221)	(0.168)	(0.283)	(0.119)
Agriculture	0.177	0.119	0.057	-0.012	0.050
	(0.156)	(0.185)	(0.218)	(0.139)	(0.247)
Metal	0.015	0.053	-0.018	0.020	0.009
	(0.074)	(0.067)	(0.050)	(0.028)	(0.059)
Live Stock	0.126	0.010	-0.108	0.245	0.058
	(0.032)	(0.113)	(0.033)	(0.139)	(0.084)

Table 3: Portfolio sorted by CDP, Basis and Momentum

This table presents the average (equally weighted) monthly returns (in percentage) of the portfolios sorted by individual CDP, Basis and Momentum. The High (Low) portfolio includes commodities in the quartile with the highest (lowest) values of a characteristic, i.e., CDP, or Basis, or Momentum. The H-L is the difference between High and Low. The t-statistics of these average monthly returns are shown in parentheses. The full sample period covers January 2001 to March 2021, the first half is January 2001 to May 2011, and the second half is June 2011 to March 2021.

Sample	Portfolio	CDP	Basis	Mom.
Full	High	0.69	0.47	0.24
		(1.93)	(1.33)	(0.70)
	Low	-0.19	0.18	0.22
		(-0.58)	(0.59)	(0.59)
	H-L	0.87	0.29	0.02
		(2.63)	(0.84)	(0.04)
1st Half	High	0.99	0.99	0.86
		(1.95)	(1.95)	(1.61)
	Low	0.04	0.05	0.10
		(0.08)	(0.12)	(0.20)
	H-L	0.93	0.94	0.76
		(1.98)	(1.91)	(1.36)
2nd Half	High	0.38	-0.08	-0.42
		(0.75)	(-0.17)	(-1.06)
	Low	-0.44	0.32	0.34
		(-1.08)	(0.73)	(0.63)
	H-L	0.82	-0.40	-0.76
		(1.73)	(-0.84)	(-1.43)

Table 4: Alphas of the CDP factor and other factors

In this table, the two columns under CDP ∼ factors present the full sample alpha (monthly) and R^2 from regressing the CDP factor on various factors, including Basis (Basis H-L returns), BasisHnL (separate Basis High portfolio and Basis Low portfolio), Momentum (Momentum H-L returns), Commodity Market (average returns of all commodities' front month futures), Carry (Koijen et al., 2018), FF5F (returns of Fama-French 5 factors), and All (all the controls). The first column under Factors ∼ CDP present the mean value of the various factor returns, and the other three columns report the alpha, beta and R^2 from time-series regressions of the various factor returns on the CDP factor, where the factors include early mentioned ones plus BasisH (Basis High portfolio) BasisL (Basis Low portfolio), Momentum (Momentum H-L returns), Commodity Market, Carry, FF5F-mkt (Fama French market factor, the excess return on the equity market), FF5F-smb (fama french size factor, the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios), FF5F-hml (fama french value factor, the average return on the two value portfolios minus the average return on the two growth portfolios), FF5F-rmw (fama french Robust Minus Weak factor, the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios), and FF5F-cma (fama french Conservative Minus Aggressive, the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios). The full sample period covers January 2001 to March 2021. The t-stats based on Newey-West standard errors are reported in parentheses. Both Mean and Alpha and their standard errors are in percentage. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

	CDP ∼ factors		Factors ∼ CDP			
Factors	Alpha	R^2	Mean	Alpha	Beta	R^2
Basis	0.75***	0.20	0.29	−0.11	0.46***	0.20
	(2.72)		(0.84)	(−0.37)	(7.58)	
BasisHnL	0.72***	0.21				
	(2.72)					
BasisH			0.47	0.16	0.35***	0.11
			(1.33)	(0.43)	(4.42)	
BasisL			0.18	0.27	−0.11*	0.01
			(0.59)	(0.80)	(−1.74)	
Momentum	0.87***	0.03	0.02	0.24	0.10**	0.02
	(2.95)		(0.04)	(−0.35)	(2.17)	
Commodity Market	0.82***	0.02	0.32	0.22	0.39*	0.16
	(2.94)		(1.24)	(0.75)	(1.65)	
Carry	0.65**	0.16	0.56*	0.48	0.20***	0.05
	(2.15)		(1.72)	(0.66)	(6.23)	
FF5F	0.73**	0.08				
	(2.40)					
FF5F-mkt			0.65**	0.48	0.20***	0.05
			(2.25)	(1.54)	(3.11)	
FF5F-smb			0.30*	0.22	0.09**	0.03
			(1.73)	(1.27)	(2.30)	
FF5F-hml			0.01	0.02	−0.01	0.00
			(0.03)	(0.07)	(−0.29)	
FF5F-rmw			0.34**	0.39**	−0.06**	0.02
			(2.40)	(2.44)	(−2.18)	
FF5F-cma			0.16	0.20	−0.05***	0.02
			(1.36)	(1.56)	(−2.78)	
All	0.63**	0.28				
	(2.24)					

Table 5: Exposures to market downside risk

The table presents Lettau, Maggiori, and Weber (2014)'s two beta estimates and their implied alpha for the four portfolios' returns: CDP, Basis, Momentum, and Commodity Market, respectively. $\beta_{LMW,mkt}$ is the full sample market beta and $\beta_{LMW,down}$ is the sub-sample market beta where the excess market return is one standard deviation below its sample mean. The implied alpha is the coefficient from regressing $\hat{y}$ on the vector of ones (without an intercept), where

$$\hat{y} = r_{\text{Portfolio}} - \beta_{LMW,mkt}\,(r_{mkt} - r_{down}) - \beta_{LMW,down}\,(r_{down})$$

and $r_{down} = 0$ if $r_{mkt} > \bar{r}_{mkt} - \sigma_{r_{mkt}}$ and $r_{down} = r_{mkt}$ otherwise, $\bar{r}_{mkt}$ and $\sigma_{r_{mkt}}$ are the sample mean and sample standard deviation of the market return, respectively. The t-stats are based on Newey-West standard errors and reported in the parentheses. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively. The implied alphas are monthly and in percentage.

Portfolio	Implied alpha	$\beta_{LMW,mkt}$	$\beta_{LMW,down}$
CDP	0.79***	0.26***	0.35
	(2.84)	(3.17)	(0.86)
Basis	0.67*	0.16*	0.65*
	(1.92)	(1.80)	(1.91)
Momentum	0.22	−0.18*	−0.10
	(0.55)	(-1.75)	(-0.27)
Commodity Market	0.72***	0.42***	1.10***
	(2.58)	(5.13)	(2.92)

Table 6: Correlations of individual CDPs

This table shows the pairwise correlations of the 24 commodity characteristics (CDPs) used in Section 5. We standardize all predictors to have zero mean and unit variance. The sample spans the period from Feb 1994 to Mar 2021.

	LGO	***C***	***KW***	***O***	***SM***	***BO***	***S***	***W***	***CC***	***KC***	***CT***	***SB***	***RR***	***OJ***	***LB***	***FC***	***LH***	***LC***	***HG***	***GC***	***PA***	***PL***	***SI***
LCO	0.29	0.30	0.31	0.32	0.20	0.03	0.26	0.40	0.15	-0.06	0.17	0.39	0.18	0.51	0.12	0.06	0.28	0.23	0.11	0.41	-0.05	0.45	-0.38
LGO		-0.13	0.31	0.06	0.40	0.14	0.47	0.54	0.03	0.23	-0.32	0.40	0.37	0.56	-0.01	0.35	0.38	0.26	0.48	0.22	-0.57	0.30	-0.57
C			0.50	0.34	-0.01	0.19	0.09	0.20	0.00	0.12	0.30	0.02	-0.41	-0.07	0.11	-0.11	-0.13	0.02	0.14	0.02	0.05	-0.12	0.04
KW				0.40	0.03	0.22	0.12	0.67	0.05	0.13	0.11	0.25	-0.18	0.10	-0.22	0.38	0.23	0.38	0.58	0.06	-0.43	-0.04	-0.52
O					0.25	0.33	0.37	0.60	0.55	0.10	0.19	0.33	0.36	0.18	0.17	0.00	0.08	0.33	0.19	0.38	-0.14	0.36	-0.22
SM						0.29	0.90	0.44	0.39	0.34	-0.19	0.35	0.51	0.38	0.22	-0.09	0.09	0.00	-0.08	0.47	-0.23	0.34	-0.04
BO							0.56	0.33	0.29	0.02	0.29	0.18	0.22	0.09	0.22	0.29	0.03	0.42	0.19	0.30	-0.02	0.19	-0.11
S								0.54	0.42	0.30	-0.08	0.42	0.56	0.45	0.25	0.02	0.09	0.17	0.00	0.56	-0.23	0.42	-0.11
W									0.50	0.23	-0.03	0.58	0.44	0.50	-0.03	0.36	0.32	0.46	0.47	0.49	-0.53	0.44	-0.67
CC										0.03	0.04	0.20	0.46	0.27	0.33	-0.13	-0.02	0.18	0.04	0.37	-0.18	0.34	-0.10
KC											-0.24	0.21	-0.05	0.18	0.08	-0.14	0.27	-0.18	0.10	0.37	0.07	0.18	-0.12
CT												0.19	-0.03	-0.08	0.05	0.24	0.03	0.33	0.16	0.10	0.16	0.04	0.01
SB													0.54	0.43	-0.05	0.29	0.31	0.41	0.29	0.50	-0.30	0.48	-0.50
RR														0.50	0.17	0.16	0.13	0.25	-0.03	0.43	-0.29	0.55	-0.24
OJ															0.22	0.15	0.48	0.19	0.28	0.60	-0.20	0.71	-0.56
LB																-0.29	-0.11	-0.07	-0.04	0.15	0.11	0.16	0.16
FC																	0.38	0.56	0.55	0.15	-0.31	0.14	-0.60
LH																		0.11	0.45	0.47	-0.03	0.57	-0.69
LC																			0.41	0.31	-0.28	0.19	-0.47
HG																				0.07	-0.39	0.14	-0.67
GC																					0.09	0.72	-0.37
PA																						0.10	0.40
PL																							-0.49

Table 7: In sample predictability: univariate and bivariate

Panel A reports slopes and $R^2s(\%)$ of the predictive regression model:

$$R_{t+1} = \alpha + \psi Z_t + \epsilon_{t+1},$$

where Z_t is either one of the 14 economic variables in Welch and Goyal (2008), the investor sentiment index of Huang et al. (2015) denoted as S (available up to Dec 2020), the short interest index of Rapach, Strauss, and Zhou (2010) denoted as SII, or our CDP aggregate predictors. Panel B reports the results from the bivariate regression

$$R_{t+1} = \alpha + \beta X_t + \psi Z_t + \epsilon_{t+1},$$

where X_t is the added regressor CDP^{PLS}, where X_t is the added regressor CDP^{PLS}. Panels C and D report similar results with CDP^{sPCA} and CDP$^{PLS+sPCA}$ as the added regressor, respectively. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

(a) Univariate

Variable	ψ (%)	R^2 (%)
dp	0.56	1.55
dy	0.60**	1.83
ep	0.15	0.11
de	0.16	0.13
svar	0.07	0.02
b/m	0.34	0.60
ntis	0.25	0.30
tbl	-0.26	0.34
lty	-0.40	0.81
ltr	0.24	0.29
tms	-0.12	0.07
dfy	-0.11	0.06
dfr	0.23	0.28
infl	0.19	0.17
SII	-0.54**	1.46
S	-0.57***	1.60
$ECON^{PLS}$	0.80***	3.20
$ECON^{sPCA}$	0.58***	1.71
$ECON^{PLS+sPCA}$	0.70***	2.44
CDP^{PLS}	0.93***	4.30
CDP^{sPCA}	0.78***	3.06
CDP$^{PLS+sPCA}$	0.87***	3.78

(b) Bivariate: adding CDP^{PLS}

Variable	β (%)	ψ (%)	R^2 (%)
dp	0.84**	0.22	4.51
dy	0.82**	0.24	4.54
ep	1.02***	-0.25	4.56
de	0.97***	0.30	4.73
svar	0.97***	0.25	4.60
b/m	0.93***	0.00	4.30
ntis	0.92***	0.03	4.30
tbl	0.91***	-0.05	4.31
lty	0.88***	-0.23	4.56
ltr	0.94***	0.28	4.69
tms	0.95***	-0.23	4.55
dfy	0.97***	0.16	4.42
dfr	0.91***	0.16	4.43
infl	0.94***	0.24	4.59
SII	0.86***	-0.15	4.38
S	0.83***	-0.24	4.45
$ECON^{PLS}$	0.70**	0.44	5.00

(c) Bivariate: adding CDP^{sPCA}

Variable	β (%)	ψ (%)	R^2 (%)
dp	0.67*	0.34	3.57
dy	0.65*	0.37	3.66
ep	0.89**	-0.24	3.29
de	0.86***	0.36	3.66
svar	0.83***	0.25	3.35
b/m	0.75**	0.09	3.10
ntis	0.77***	0.03	3.06
tbl	0.76**	-0.14	3.15
lty	0.74**	-0.32*	3.55
ltr	0.79***	0.27	3.44
tms	0.80***	-0.20	3.26
dfy	0.83***	0.17	3.18
dfr	0.77***	0.18	3.22
infl	0.78**	0.19	3.25
SII	0.83**	-0.23	3.27
S	0.67**	-0.38**	3.66
$ECON^{sPCA}$	0.66*	0.35	3.61

(d) Bivariate - GW and Indices: CDP$^{PLS+sPCA}$

Variable	β (%)	ψ (%)	R^2 (%)
dp	0.77**	0.27	4.10
dy	0.75**	0.30	4.15
ep	0.98***	-0.26	4.06
de	0.93***	0.33	4.32
svar	0.92***	0.26	4.09
b/m	0.86***	0.03	3.78
ntis	0.86***	0.02	3.78
tbl	0.85***	-0.09	3.82
lty	0.83***	-0.27	4.14
ltr	0.88***	0.28	4.16
tms	0.89***	-0.22	4.01
dfy	0.92***	0.18	3.92
dfr	0.85***	0.17	3.92
infl	0.88***	0.22	4.01
SII	0.79***	-0.18	3.90
S	0.76***	-0.31	4.12
$ECON^{PLS+sPCA}$	0.69*	0,39	4,38

Table 8: In sample results: controlling for various uncertainties

This table reports the results of the bivariate regression:

$$R_{t+1} = \alpha + \beta X_t + \psi Z_t + \epsilon_{t+1},$$

for predicting the market excess returns, where X(t) denotes aggregate CDP predictors (CDP^{PLS}) in Panel A, sPCA (CDP^{sPCA}) in Panel B, and PLS+sPCA (CDP$^{PLS+sPCA}$) in Panel C, and Z_t represents the financial uncertainty measure (FU) of Jurado, Ludvigson, and Ng (2015), the macroeconomic uncertainty measure (MacroU) of Jurado, Ludvigson, and Ng (2015), the economic policy uncertainty measure (EPU) of Baker, Bloom, and Davis (2016), the uncertainty measure (UBEX) of Bekaert, Engstrom, and Xu (2014), as well as the "model-free" implied variance (IV), the "model-free" realized variance (RV), the variance risk premium (VRP), the expected variance risk premium (EVRP), and the expected realized variance (ERV) of Bollerslev, Tauchen, and Zhou (2009). ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP^{PLS}			Panel B: CDP$^{PLS+sPCA}$			Panel C: Z_t		
Variables	β(%)	ψ(%)	R^2_{OS}(%)	β(%)	ψ(%)	R^2_{OS} (%)	β(%)	ψ(%)	R^2_{OS}(%)
IV	1.07***	0.54	5.69	0.96***	0.56	4.51	1.03***	0.57	5.26
RV	0.98***	0.32	4.80	0.84***	0.32	3.56	0.93***	0.33	4.30
VRP	0.93***	0.08	4.33*	0.78***	0.09	3.10	0.87***	0.09	3.82
EVRP	0.85***	-0.40	5.04*	0.69***	-0.41	3.87.	0.79***	-0.40	4,53
ERV	1.02***	0.84**	7.78	0.91***	0.86**	6.70	0.98***	0.86**	7.38
FU	0.90***	-0.07	4.32*	0.73***	-0.12	3.11	0.83***	-0.98	3.80
MacroU	0.94****	0.06	4.31**	0.80***	0.06	3.08	0.89***	0.07	3.80
EPU	0.85***	0.55**	5.8.	0.72***	0.59**	4.80	0.80***	0.57**	5.38
UBEX	1.05***	0.38	4.95	0.91***	0.36	3.65	1.00***	0.39	4.44

Table 9: In sample: Pre- and Post- financialisation

This table reports the slopes and in-sample R^2s of the univariate predictive regression:

$$R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1},$$

for predicting the market excess returns, where X_t represents aggregate CDP predictors constructed with PLS (CDP^{PLS}), sPCA (CDP^{sPCA}) and PLS+sPCA (CDP$^{PLS+sPCA}$), respectively. The sample spans the period from Feb 1994 to Dec 2000 in Panel A (pre-financialization) and from Jan 2001 to Mar 2021 (post-financialization) in Panel B. ***, **, and * indicate significance at 1%, 5% and 10% levels, respectively. We standardize all predictors to have zero mean and unit variance.

	Panel A: Pre-finalization		Panel B: Post-financialization	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
CDP^{PLS}	0.93***	4.49	1.15***	6.45
CDP^{sPCA}	0.96***	4.62	1.02***	5.10
CDP$^{PLS+sPCA}$	0.96***	4.66	1.11***	6.01

Table 10: Out-of-sample results

This table reports the out-of-sample R^2_{OS}'s and MSFE-adjusted statistics for predicting the average excess stock market returns over the prediction horizon h by using aggregate predictors based on CDPs and the 14 economic variables in Welch and Goyal (2008) constructed with PLS (CDP^{PLS} & $ECON^{PLS}$) in Panel A, sPCA (CDP^{sPCA} & $ECON^{sPCA}$) in Panel B, and the dynamic combination strategy of PLS and sPCA (CDP$^{PLS+sPCA}$ & $ECON^{PLS+sPCA}$) in Panel C. $h = 1$ month, 3, 6, 9, 12, 18, and 24 months. Statistical significance for the R^2_{OS}'s is based on the p-value of Clark and West (2007) MSFE-adjusted statistic. The sample spans the period from Feb 1994 to Mar 2021. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Panel A		Panel B		Panel C	
	CDP^{PLS}		CDP^{sPCA}		CDP$^{PLS+sPCA}$	
Horizon	R^2_{OS} (%)	MSFE-adjusted	R^2_{OS} (%)	MSFE-adjusted	R^2_{OS} (%)	MSFE-adjusted
h=1	1.07*	1.31	1.14	1.01	1.22	1.21
h=6	6.19**	2.17	5.50	1.17	11.74***	1.99
h=12	8.19*	1.59	3.94*	1.11	15.10**	2.02
h=18	13.16*	1.39	3.54*	1.28	19.83**	1.77
h=24	21.67*	1.48	4.05*	1.35	25.04***	1.69
	$ECON^{PLS}$		$ECON^{sPCA}$		$ECON^{PLS+sPCA}$	
Horizon	R^2_{OS} (%)	MSFE-adjusted	R^2_{OS} (%)	MSFE-adjusted	R^2_{OS} (%)	MSFE-adjusted
h=1	-6.08	-0.52	-23.25	-1.10	-22.66	-1.04
h=6	-24.17	-0.43	-65.54	-1.11	-19.72	-0.44
h=12	-43.76	-0.3	-97.54	-0.99	-34.4	-0.34
h=18	-1.14	1.33	-2.22	0.56	22.64**	1.70
h=24	-9.37	1.42	-7.51	0.21	16.48*	1.40

Table 11: Economic values

This table reports the annualized CER gains (in %) and annualized Sharpe ratios for a mean-variance investor with a risk-aversion coefficient of five, for predicting future market excess returns by using aggregate predictors based on CDPs and the 14 economic variables in Welch and Goyal (2008) constructed with PLS (CDP^{PLS} & $ECON^{PLS}$) in Panel A, sPCA (CDP^{sPCA} & $ECON^{sPCA}$) in Panel B, and the dynamic combination strategy of PLS and sPCA ($\text{CDP}^{PLS+sPCA}$ & $ECON^{PLS+sPCA}$) in Panel C, relative to historical mean returns. We consider three cases: zero transaction cost and a proportional transaction cost of 25 and 50 basis points per transaction. The sample spans the period from Feb 1994 to Mar 2021.

	TCs=0 bps		TCs=25 bps		TCs=50 bps	
Panel A: PLS	CER gain (%)	SR	CER gain (%)	SR	CER gain (%)	SR
CDP^{PLS}	1.5	0.88	1.26	0.86	1.02	0.84
$ECON^{PLS}$	0.81	0.84	0.36	0.81	-0.09	0.77
Panel B: sPCA	CER Gain (%)	SR	CER Gain (%)	SR	CER Gain (%)	SR
CDP^{sPCA}	0.36	0.82	0.14	0.8	-0.07	0.78
$ECON^{sPCA}$	-2.00	0.65	-2.64	0.6	-3.28	0.55
Panel C: PLS+sPCA	CER Gain (%)	SR	CER Gain (%)	SR	CER Gain (%)	SR
$\text{CDP}^{PLS+sPCA}$	1.46	0.88	1.12	0.85	0.77	0.82
$ECON^{PLS+sPCA}$	-1.1	0.72	-1.84	0.67	-2.59	0.62

Table 12: Out-of-sample results based on alternative aggregation approaches

This table reports the out-of-sample R^2_{OS}'s and MSFE-adjusted statistics for predicting the average excess stock market returns over the prediction horizon h by constructing CDP predictors with C-ENet (Panel A), simple average combination (Panel B), and Ridge (Panel C). h=1 month, 3, 9, 12, 18, and 24 months. Statistical significance for the R^2_{OS}'s is based on the p-value of Clark and West (2007) MSFE-adjusted statistic. The sample spans the period from Feb 1994 to Mar 2021. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: CDP^{C-ENet}		Panel B: CDP^{Ave}		Panel C: CDP^{Ridge}	
Horizon	R^2_{OS} (%)	MSFE-adjusted	R^2_{OS} (%)	MSFE-adjusted	R^2_{OS} (%)	MSFE-adjusted
h=1	1.41*	1.44	0.14	0.81	0.06*	1.53
h=6	7.71*	1.33	1.15*	1.40	0.50*	1.55
h=12	3.02*	1.28	1.38	1.09	0.88*	1.54
h=18	1.55*	1.57	2.85*	1.31	1.50*	1.61
h=24	3.39**	1.92	4.71**	1.68	2.35**	2.19

Table 13: Economic channels of CDP predictability

This table reports the estimates of the predictive regression for three estimated stock return components of the period from February 1994 to March 2021,

$$y_{t+1} = \alpha + \beta x_t + \epsilon_t,$$

where x_t is one of the CDP indices and y_t is one of the three estimated components of the stock return, which are the expected return ($E_t(R_{t+1})$, cash flow news (η_{t+1}^{DR}) and discount rate news (η_{t+1}^{DR}), with corresponding betas, β_E, β_{CF}, and β_{DR}, respectively. The last row reports the OLS regression coefficient of the log stock index return on x_t, whose beta satisfies $\beta = \beta_E + \beta_{CF} - \beta_{DR}$ from the OLS properties. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CDP^{PLS}			CDP^{sPCA}			$\text{CDP}^{PLS+sPCA}$		
VAR variables	β_E	β_{CF}	β_{DR}	β_E	β_{CF}	β_{DR}	β_E	β_{CF}	β_{DR}
r, DP	0.31***	0.41***	-0.24	0.25***	0.39***	-0.18	0.29***	0.40***	-0.21
r, DP, DY	0.30***	0.41***	-0.25	0.24***	0.39***	-0.19	0.28***	0.40***	-0.21
r, DP, EP	0.36***	0.58***	-0.02	0.31***	0.49**	-0.02	0.34***	0.54**	-0.02
r, DP, DE	0.36***	0.58***	-0.02	0.31***	0.49**	-0.02	0.34***	0.54**	-0.02
r, DP, RVOL	0.30***	0.40***	-0.25	0.25***	0.38***	-0.19	0.28***	0.40***	-0.22
r, DP, BM	0.31***	0.48***	-0.17	0.25***	0.40***	-0.16	0.29***	0.45***	-0.17
r, DP, NTIS	0.45***	0.41***	-0.10	0.41***	0.37***	-0.03	0.44***	0.40***	-0.06
r, DP, TBL	0.31***	0.34**	-0.31*	0.26***	0.32**	-0.24*	0.29***	0.33**	-0.28*
r, DP, LTY	0.34***	0.37**	-0.24	0.27***	0.35**	-0.19	0.31***	0.37**	-0.22
r, DP, LTR	0.31***	0.41***	-0.24	0.25***	0.39***	-0.18	0.28***	0.40***	-0.21
r, DP, TMS	0.31***	0.42***	-0.23	0.25***	0.40***	-0.17	0.29***	0.41***	-0.20
r, DP, DFY	0.49***	0.37**	-0.10	0.44***	0.37**	-0.00	0.47***	0.38**	-0.05
r, DP, DFR	0.30***	0.41***	-0.25	0.25***	0.38***	-0.18	0.28***	0.40***	-0.22
r, DP, INFL	0.31***	0.41***	-0.24	0.26***	0.39***	-0.17	0.29***	0.41***	-0.21
r, DP, PC	0.40***	0.50**	-0.06	0.36***	0.41**	-0.05	0.38***	0.46**	-0.05
OLS		0.96***			0.82***			0.90***	

Table 14: CDPs' predictability on inflation

This table reports the results of the CDP indices' predictability on inflation. The ARMA model is specified as: $y_t = \alpha + \beta \Delta\text{CDP}^k_{t-3} + \theta_1 y_{t-1} + \theta_2 \epsilon_{t-1} + \epsilon_t, k = PLS, sPCA, PLS + sPCA$, where y_t is the difference in consumer price inflation (CPI) for all urban consumers at t and $t+1$. ΔCDP_{t-3} is the difference between t and $t-3$ CDP index. Four model specifications are considered: inflation-only and inflation with one of the three CDP indices. The values in parenthesis report the t statistics for parameters. AIC is the Akaike information criterion. $logL$ is the maximized loglikelihood function of each model estimation. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Models	$\alpha(\%)$	θ_1	θ_2	$\beta(\%)$	AIC	$logL$
Inflation only	0.18***	0.23***	0.36***		-2840	1424
	(6.19)	(2.84)	(4.88)			
Inflation+ CDP^{PLS}	0.18***	0.19**	0.37***	-0.12***	-2845	1428
	(6.49)	(2.22)	(4.65)	(-2.44)		
Inflation+ CDP^{sPCA}	0.18***	0.20**	0.37***	-0.07*	-2842	1426
	(6.37)	(2.31)	(4.77)	(-1.78)		
Inflation+ CDP$^{PLS+sPCA}$	0.18***	0.19**	0.37***	-0.10**	-2844	1427
	(6.44)	(2.23)	(4.71)	(-2.18)		

Supplementary (Online) Appendix: A Model-based Commodity Risk Measure on Commodity and Stock Market Returns

Ai Jun Hou, Emmanouil Platanakis, Xiaoxia Ye, & Guofu Zhou

A Kalman filter

We present a bespoke KF procedure designed for our estimation method outlined in Section 3.2. For more general KF references, please see Harvey (1989, Chapter 3) and Hamilton (1994, Chapter 13). We start the KF by choosing the initial values of the state variables and their covariance matrix as their steady state values $Y_{0|0} = [r_0, \delta_0, X_0]^\intercal$, and $P_{Y,0|0} = 0_{3\times3}$, where r_0 is the Treasury yield with the shortest maturity on the first day of the sample, X_0 is the log of the front month futures price on the first day of the sample, δ_0 is a free parameter to be estimated alongside other parameters. Given $Y_{t-h|t-h}$ and $P_{Y,t-h|t-h}$, the *ex ante* prediction of the state variables and their covariance matrix are given by

$$Y_{t|t-h} = e^{K_1^{\mathbb{P}} h} Y_{t-h|t-h} \text{ and } P_{Y,t|t-h} = e^{K_1^{\mathbb{P}} h} P_{Y,t-h|t-h} \left(e^{K_1^{\mathbb{P}} h}\right)^\intercal + \varOmega(K_1^{\mathbb{P}}, h),$$

Given $Y_{t|t-h}$ and $P_{Y,t|t-h}$, the *ex ante* predictions of the measurement and the associated covariance become

$$\begin{aligned}
\log\left(\overline{F}_{t|t-h}^{\Delta t}\right) &= \frac{\iota^\intercal \varOmega\left(K_1, \Delta t\right)\iota}{2} + \iota^\intercal\left[\exp(K_1 \Delta t) - I\right] K_1^{-1} K_0 + \iota^\intercal \exp(K_1 \Delta t) Y_{t|t-h} \\
P_{\log\left(\overline{F}_t^{\Delta t}\right)} &= M P_{Y,t|t-1} M^\intercal + \xi I_{n_t \times n_t},
\end{aligned}$$

where M is $n_t \times 3$ and its ith row is $\iota^\intercal \exp(K_1 \Delta t_i)$ with Δt_i being the time to maturity of the ith futures on day t and $i = 1, 2, \ldots, n_t$. Finally, the *ex post* updates on the filtered state variables are given by

$$Y_{t|t} = Y_{t|t-h} + \varXi_t\left(\log\left(\overline{F}_t^{\Delta t}\right) - \log\left(\overline{F}_{t|t-h}^{\Delta t}\right)\right) \text{ and } P_{Y,t|t} = P_{Y,t|t-h} - \varXi_t P_{\log\left(\overline{F}_t^{\Delta t}\right)} \varXi_t^\intercal,$$

where $\varXi_t = P_{Y,t|t-1} M P^{-1}_{\log\left(\overline{F}_t^{\Delta t}\right)}$ is the Kalman gain. $Y_{t|t}$ is used to compute the RP_t on day t.

B Technical details on forecasting stock index

B.1 Partial least square (PLS)

We consider the following one-period forecasting model:

$$R_{t+1} = \alpha + \beta \mathrm{CDP}_t^* + \epsilon_{t+1} \tag{B.1}$$

where R_{t+1} denotes the excess stock market return at $t+1$. CDP_t^* represents the true but unobservable aggregate CDP at t that matters for forecasting R_{t+1} and ϵ_{t+1} is a noise term unrelated to CDP_t^*. Assume the following factor structure for the commodity characteristics ($\mathrm{CDP}_{i,t}, i = 1, 2, ...N$),

$$\mathrm{CDP}_{i,t} = n_{i,0} + n_{i,1}\mathrm{CDP}_t^* + n_{i,2}\mathrm{x}Error_t + e_{i,t}, \quad i = 1, \ldots, N \tag{B.2}$$

where CDP_t^* is the unobservable aggregate index in equation (B.1) that matters for forecasting. $n_{i,1}$ is the regression slope that captures the sensitivity of each $CDP_{i,t}$ ($i = 1, ..., N$) to the unobservable index CDP_t^*. $Error_t$ is the common approximation error component of all commodity characteristics that is irrelevant to stock returns, and $e_{i,t}$ represents idiosyncratic noise.

Our aim here is to efficiently estimate the relevant for forecasting, but unobservable, aggregate index CDP_t^* by imposing a factor structure equation (B.2) on the commodity characteristics ($CDP_{i,t}$, $i = 1, ..., N$), and filtering out the irrelevant components $Error_t$ and e_{it} when estimating CDP_t^*. Hence, we consider a popular information aggregating method, the Partial Least Squares (PLS). PLS is an efficient technique for constructing aggregate predictors as shown in Kelly and Pruitt (2013, 2015), and Light, Maslov, and Rytchkov (2017), among others.

To extract CDP_t^*, PLS exploits the covariance between CDP_t^* and future stock market returns, and uses a linear combination of individual $CDPs$ ($i = 1, ..., N$) for predicting stock returns. PLS follows a two-step process involving a time-series regression in the first step and a cross-sectional regression in the second step. In the first step, the time-series regression of each CDPs ($i = 1, ..., N$) on a constant and future excess stock returns (R_{t+1}) has the following form:

$$\mathrm{CDP}_i, t = \pi_0 + \pi_i R_{t+1} \mu_{i,t}, \text{ for } i = 1, \ldots, N \tag{B.3}$$

where the regression slope π_i captures the sensitivity of each CDP to the unobservable aggregate index CDP_t^*. Since the latter drives the future stock market returns as shown in equation (B.1), each CDP_i, t is unrelated with any unforecastable errors, and hence the slope $\pi_{i,1}$ is a good approximation on how each CDP_i, t depends on the unobservable aggregate index CDP_t^*.

In the second step, the cross-sectional regression is as follows:

$$\mathrm{CDP}_{i,t} = c_0 + \mathrm{Com}_t^{PLS} \hat{\pi}_i + v_{i,t}, \text{ for } i = 1, \ldots, N \tag{B.4}$$

where the independent variable ($\hat{\pi}_i$) in regression equation (B.3) has been estimated during the first step of the PLS method in regression equation (B.3). The aggregate PLS index (Com^{PLS}) is the slope in regression equation (B.4) to be estimated.

B.2 Scaled Principal Component Analysis (sPCA)

The sPCA is implemented in two steps. First, we construct a panel of scaled CDP predictors as: ($\beta_1 CDP_{1t}, ..., \beta_n CDP_{Nt}$), where the scaled coefficients ($\beta_i, i = 1, ..., N$) are estimated via the following predictive regression of the future stock excess returns (R_{t+1}) on the i_{th} commodity characteristic ($CDP_{i,t}$):

$$R_{t+1} = \alpha_i + \beta_i \mathrm{CDP}_{i,t} + \epsilon_{t+1} \text{ for } i = 1, dot, N \tag{B.5}$$

In the second step, the conventional PCA is applied to ($\beta_1 CDP_{1t}, ..., \beta_n CDP_{Nt}$), and the sPCA-based aggregate CDP predictor, CDP^{sPCA} is computed by using the first three principal components. Intuitively, ($\beta_i \mathrm{CDP}_{i,t}$) reflects the predictive power of the i_{th} commodity characteristic ($\mathrm{CDP}_{i,t}$) on the future returns, and hence sPCA constructs (CDP^{sPCA})

by over- (under-) weighting the commodity characteristics with strong (weak) forecasting power.

C Detailed description of economic variables

In the predictive channel section, we use the following 14 economic variables of Welch and Goyal (2008):

- Dividend-price ratio (log), DP: log of a 12-month moving sum of dividends paid on the S& P 500 index minus the log of stock prices (S&P 500 index).
- Dividend yield (log), DY: log of a 12-month moving sum of dividends minus the log of lagged stock prices.
- Earnings-price ratio (log), EP: log of a 12-month moving sum of earnings on the S&P 500 index minus the log of stock prices.
- Dividend-payout ratio (log), DE: log of a 12-month moving sum of dividends minus the log of a 12-month moving sum of earnings.
- Stock return variance, SVAR: sum of squared daily returns on the S&P 500 index.
- Book-to-market ratio, BM: ratio of book value to market value for the Dow Jones Industrial Average.
- Net equity expansion, NTIS: ratio of a 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.
- Treasury bill rate, TBL: interest rate on a 3-month Treasury bill (secondary market).
- Long-term yield, LTY: long-term government bond yield.
- Long-term return, LTR: return on long-term government bonds.
- Term spread, TMS: long-term yield minus the Treasury bill rate.

- Default yield spread, DFY: difference between BAA- and AAA-rated corporate bond yields.
- Default return spread, DFR: long-term corporate bond return minus the long-term government bond return.
- Inflation, INFL: calculated from the consumer price inflation (CPI) for all urban consumers; we use lagged 2-month inflation in the regression to account for the delay in CPI releases.

D Additional results

Table A1: Portfolio sorting with individual CDP, Basis and Momentum (quintile results)

This table presents the average (equally weighted) monthly returns (in percentage) of the portfolios sorted by individual CDP, Basis and Momentum. The High (Low) portfolio includes commodities in the quintile with the highest (lowest) values of a characteristic, i.e., CDP, Basis, or Momentum. The H-L is the difference between High and Low. The t-statistics of these average monthly returns are shown in the parentheses. The full sample period covers January 2001 to March 2021, the first half is January 2001 to May 2011, and the second half is June 2011 to March 2021.

Sample	Portfolio	CDP	Basis	Mom.
Full	High	0.65	0.43	0.26
		(1.71)	(1.21)	(0.77)
	Low	-0.08	0.21	0.24
		(-0.24)	(0.68)	(0.61)
	H-L	0.73	0.21	0.02
		(2.03)	(0.61)	(0.06)
1st Half	High	0.93	0.99	0.75
		(1.74)	(1.90)	(1.38)
	Low	0.14	-0.02	0.12
		(0.27)	(-0.06)	(0.22)
	H-L	0.77	1.02	0.63
		(1.62)	(2.03)	(1.10)
2nd Half	High	0.36	-0.17	-0.25
		(0.67)	(-0.35)	(-0.61)
	Low	-0.31	0.47	0.37
		(-0.72)	(1.01)	(0.63)
	H-L	0.67	-0.63	-0.62
		(1.25)	(-1.31)	(-1.04)

Table A2: In sample: univariate regression using 10 industry portfolios – PLS

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 10 industry portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$, where X_t represents aggregate predictors (by using PLS) extracted either from commodity characteristics (CDP^{PLS}) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{PLS}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP^{PLS}		Panel B: $ECON^{PLS}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Non-durable	0.53***	2.05	0.51**	1.91
Durable	1.14**	2.08	1.24***	2.49
Manufacture	0.78***	2.51	0.65***	1.76
Energy	0.65*	0.95	0.17	0.07
Technology	1.13**	2.62	1.11*	2.51
Telecom	1.12***	4.69	1.02***	3.88
Shop	0.64***	2.01	0.68***	2.28
Health	0.71***	2.78	0.62**	2.11
Utility	0.39	0.9	0.17	0.17
Other	0.99***	3.49	0.72***	1.86

Table A3: In sample: univariate regression using 10 industry portfolios – sPCA

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 10 industry portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$,where X_t represents aggregate predictors (by using sPCA) extracted either from commodity characteristics (CDP^{sPCA}) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{sPCA}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP^{sPCA}		Panel B: $ECON^{sPCA}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Non-durable	0.59***	2.50	0.35	0.91
Durable	0.87	1.23	0.83*	1.10
Manufacture	0.72**	2.14	0.44	0.81
Energy	0.69**	1.10	0.03	0.00
Technology	0.81*	1.33	0.90	1.65
Telecom	0.84**	2.65	0.79*	2.37
Shop	0.52**	1.31	0.48**	1.12
Health	0.69***	2.62	0.49*	1.35
Utility	0.38	0.88	0.03	0.01
Other	0.95**	3.20	0.43	0.67

Table A4: In sample: univariate regression using 10 industry portfolios – PLS+sPCA

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 10 industry portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$,where X_t represents aggregate predictors (by using PLS+ sPCA) extracted either from commodity characteristics (CDP$^{PLS+sPCA}$) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{PLS+sPCA}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP$^{PLS+sPCA}$		Panel B: $ECON^{PLS+sPCA}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Non-durable	0.57***	2.35	0.44**	1.39
Durable	1.02*	1.68	1.04**	1.75
Manufacture	0.77**	2.4	0.55**	1.26
Energy	0.68*	1.06	0.1	0.02
Technology	0.99**	1.98	1.01	2.09
Telecom	1.00***	3.72	0.91**	3.14
Shop	0.59***	1.7	0.59***	1.68
Health	0.71***	2.79	0.56**	1.74
Utility	0.39	0.92	0.1	0.06
Other	0.98***	3.46	0.58**	1.21

Table A5: In sample: univariate regression using 17 industry portfolios – PLS

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 17 industry portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$, where X_t represents aggregate predictors (by using PLS) extracted either from commodity characteristics (CDP^{PLS}) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{PLS}$) - Panel B. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP^{PLS}		Panel B: $ECON^{PLS}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Food	0.51***	1.77	0.51**	1.75
Mines	0.44	0.29	0.32	0.16
Oil	0.67*	1.01	0.21	0.1
Clothing	0.67**	1.23	0.94***	2.43
Durable	0.99***	2.76	1.10***	3.4
Chemicals	0.81**	1.81	0.94***	2.41
Consumption	0.65***	2.65	0.57***	2.04
Construction	0.90***	2.25	0.91***	2.32
Steel	1.10*	1.56	0.73	0.69
Fabric	0.80**	2.03	0.80***	2.03
Machinery	1.06**	2.18	0.95	1.73
Cars	1.04**	1.97	1.13***	2.37
Transportation	0.82***	2.39	0.72***	1.84
Utility	0.39	0.9	0.17	0.17
Retail	0.61***	1.7	0.63***	1.85
Finance	0.98**	2.96	0.67**	1.38
Other	1.07***	4.48	1.00***	3.96

Table A6: In sample: univariate regression using 17 industry portfolios – sPCA

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 17 industry portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$, where X_t represents aggregate predictors (by using sPCA) extracted either from commodity characteristics (CDP^{sPCA}) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{sPCA}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP^{sPCA}		Panel B: $ECON^{sPCA}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Food	0.58***	2.31	0.38*	0.98
Mines	0.35	0.18	0.14	0.03
Oil	0.71**	1.14	0.06	0.01
Clothing	0.71**	1.36	0.64*	1.11
Durable	0.90**	2.26	0.81**	1.87
Chemicals	0.78**	1.65	0.74**	1.49
Consumption	0.62***	2.44	0.45*	1.3
Construction	0.78**	1.68	0.64**	1.15
Steel	0.99	1.26	0.44	0.25
Fabric	0.80**	2.03	0.58*	1.08
Machinery	0.75	1.07	0.74	1.07
Cars	0.77	1.08	0.77**	1.09
Transportation	0.81***	2.29	0.50*	0.89
Utility	0.38	0.88	0.03	0.01
Retail	0.47*	1.02	0.44*	0.88
Finance	0.98**	2.93	0.37	0.42
Other	0.85**	2.83	0.77*	2.33

Table A7: In sample: univariate regression using 17 industry portfolios – PLS+sPCA

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 17 industry portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$, where X_t represents aggregate predictors (by using sPCA) extracted either from commodity characteristics (CDP$^{PLS+sPCA}$) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{PLS+sPCA}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP$^{PLS+sPCA}$		Panel B: $ECON^{PLS+sPCA}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Food	0.56***	2.1	0.45**	1.36
Mines	0.4	0.24	0.23	0.08
Oil	0.70**	1.11	0.14	0.04
Clothing	0.70**	1.34	0.80**	1.74
Durable	0.96***	2.59	0.96***	2.63
Chemicals	0.81**	1.79	0.84***	1.96
Consumption	0.65***	2.63	0.52**	1.68
Construction	0.85***	2.02	0.78***	1.71
Steel	1.06*	1.45	0.59	0.45
Fabric	0.81**	2.10	0.69***	1.54
Machinery	0.92*	1.63	0.85	1.41
Cars	0.92**	1.54	0.96**	1.7
Transportation	0.83***	2.42	0.62**	1.34
Utility	0.39	0.92	0.10	0.06
Retail	0.55**	1.39	0.54**	1.35
Finance	1.00**	3.04	0.52*	0.85
Other	0.97***	3.73	0.89**	3.15

Table A8: In sample: univariate regression using 10 size portfolios – PLS

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 10 size portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$, where X_t represents aggregate predictors (by using PLS) extracted either from commodity characteristics (CDP^{PLS}) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{PLS}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP^{PLS}		Panel B: $ECON^{PLS}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Small	0.75*	1.37	0.35	0.30
2	0.76*	1.26	0.40	0.35
3	0.80**	1.64	0.66**	1.13
4	0.81***	1.83	0.71**	1.42
5	0.81**	1.91	0.69**	1.39
6	0.85***	2.52	0.82***	2.35
7	0.81**	2.37	0.65**	1.53
8	0.77**	2.27	0.67**	1.70
9	0.83***	3.24	0.69**	2.27
Large	0.96***	5.01	0.82***	3.66

Table A9: In sample: univariate regression using 10 size portfolios – sPCA

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 10 size portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$, where X_t represents aggregate predictors (by using PLS) extracted either from commodity characteristics (CDP^{sPCA}) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{sPCA}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP^{sPCA}		Panel B: $ECON^{sPCA}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Small	0.77*	1.45	0.15	0.06
2	0.73*	1.15	0.2	0.08
3	0.75**	1.45	0.46	0.54
4	0.73**	1.49	0.5	0.6991
5	0.71**	1.48	0.48	0.66
6	0.77***	2.05	0.63**	1.38
7	0.76**	2.1	0.43	0.66
8	0.69*	1.84	0.43	0.7
9	0.74**	2.55	0.48	1.07
Large	0.80***	3.43	0.61*	1.99

Table A10: In sample: univariate regression using 10 size portfolios – PLS+sPCA

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 10 size portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$, where X_t represents aggregate predictors (by using PLS) extracted either from commodity characteristics (CDP$^{PLS+sPCA}$) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{PLS+sPCA}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP$^{PLS+sPCA}$		Panel B: $ECON^{PLS+sPCA}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Small	0.77*	1.45	0.25	0.16
2	0.75*	1.24	0.30	0.20
3	0.79**	1.60	0.56*	0.82
4	0.78***	1.71	0.61**	1.04
5	0.77**	1.75	0.59*	1.01
6	0.82***	2.36	0.73***	1.86
7	0.80**	2.31	0.54*	1.07
8	0.74**	2.12	0.55*	1.17
9	0.80**	2.98	0.59**	1.65
Large	0.89***	4.33	0.72**	2.81

Table A11: In sample: univariate regression using 10 book-to-market portfolios – PLS

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 10 book-to-market portfolio. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$, where X_t represents aggregate predictors (by using PLS) extracted either from commodity characteristics (CDP^{PLS}) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{PLS}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP^{PLS}		Panel B: $ECON^{PLS}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Growth	0.98***	4.17	0.97***	4.11
2	0.84***	3.62	0.75***	2.86
3	0.73***	2.96	0.57***	1.80
4	0.80***	3.05	0.64***	1.96
5	0.74***	2.78	0.56***	1.62
6	0.78**	2.68	0.53**	1.24
7	0.89**	3.3	0.48**	0.96
8	0.79**	2.24	0.38	0.53
9	0.82**	2.19	0.64**	1.34
Value	0.82**	1.45	0.49*	0.52

Table A12: In sample: univariate regression using 10 book-to-market portfolios – sPCA

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 10 book-to-market portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$, where X_t represents aggregate predictors (by using PLS) extracted either from commodity characteristics (CDP^{sPCA}) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{sPCA}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP^{sPCA}		Panel B: $ECON^{sPCA}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Growth	0.78**	2.65	0.76*	2.5
2	0.70***	2.48	0.53*	1.44
3	0.63**	2.2	0.36	0.72
4	0.78***	2.92	0.42*	0.85
5	0.68***	2.41	0.37*	0.72
6	0.75**	2.53	0.29	0.38
7	0.91*	3.41	0.2	0.17
8	0.77**	2.15	0.11	0.04
9	0.82**	2.18	0.41	0.54
Value	0.80*	1.4	0.21	0.09

Table A13: In sample: univariate regression using 10 book-to-market portfolios – PLS+sPCA

This table reports the results (slopes and in-sample R^2's (%)) of a univariate predictive regression for predicting the monthly excess returns of the 10 book-to-market portfolios. The regression is: $R_{t+1} = \alpha + \psi X_t + \epsilon_{t+1}$, where X_t represents aggregate predictors (by using PLS) extracted either from commodity characteristics (CDP$^{PLS+sPCA}$) - Panel A, or from the 14 economic variables in Welch and Goyal (2008) ($ECON^{PLS+sPCA}$) - Panel B. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021. We standardize all predictors to have zero mean and unit variance.

	Panel A: CDP$^{PLS+sPCA}$		Panel B: $ECON^{PLS+sPCA}$	
Variables	ψ(%)	R^2(%)	ψ(%)	R^2(%)
Growth	0.90***	3.48	0.87**	3.31
2	0.78***	3.12	0.64**	2.12
3	0.70***	2.65	0.47**	1.22
4	0.80***	3.08	0.53***	1.37
5	0.72***	2.68	0.47**	1.14
6	0.78**	2.69	0.41*	0.76
7	0.91**	3.47	0.34	0.49
8	0.79**	2.27	0.25	0.23
9	0.83**	2.26	0.53	0.92
Value	0.82**	1.47	0.35	0.27

Table A14: Economic value results: risk aversion=3

This table reports the annualized CER gains (in %) and annualized Sharpe ratios for a mean-variance investor with a risk-aversion coefficient of three, for predicting future market excess returns by using aggregate predictors based on CDPs and the 14 economic variables in Welch and Goyal (2008) constructed with PLS (CDP^{PLS} & $ECON^{PLS}$) in Panel A, sPCA (CDP^{sPCA} & $ECON^{sPCA}$) in Panel B, and the dynamic combination strategy of PLS and sPCA: ($CDP^{PLS+sPCA}$ & $ECON^{PLS+sPCA}$) in Panel C, relative to historical mean returns. We consider three cases: zero transaction cost and a proportional transaction cost of 25 and 50 basis points per transaction. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021.

	TCs=0 bps		TCs=25 bps		TCs=50 bps	
Panel A: PLS	CER gain (%)	SR	CER gain (%)	SR	CER gain (%)	SR
CDP^{PLS}	0.95	0.88	0.91	0.88	0.88	0.87
$ECON^{PLS}$	-1.55	0.77	-1.88	0.75	-2.21	0.73
Panel B: sPCA	CER Gain (%)	SR	CER Gain (%)	SR	CER Gain (%)	SR
CDP^{sPCA}	2.19	0.93	2.2	0.93	2.2	0.92
$ECON^{sPCA}$	-4.92	0.61	-5.41	0.57	-5.9	0.54
Panel C: PLS+sPCA	CER Gain (%)	SR	CER Gain (%)	SR	CER Gain (%)	SR
CDP$^{PLS+sPCA}$	1.75	0.92	1.74	0.91	1.72	0.91
$ECON^{PLS+sPCA}$	-2.46	0.73	-2.96	0.7	-3.46	0.67

Table A15: Economic value results: risk aversion=4

This table reports the annualized CER gains (in %) and annualized Sharpe ratios for a mean-variance investor with a risk-aversion coefficient of four, for predicting future market excess returns by using aggregate predictors based on CDPs and the 14 economic variables in Welch and Goyal (2008) constructed with PLS (CDP^{PLS} & $ECON^{PLS}$) in Panel A, sPCA (CDP^{sPCA} & $ECON^{sPCA}$) in Panel B, and the dynamic combination strategy of PLS and sPCA: ($CDP^{PLS+sPCA}$ & $ECON^{PLS+sPCA}$) in Panel C, relative to historical mean returns. We consider three cases: zero transaction cost and a proportional transaction cost of 25 and 50 basis points per transaction. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021.

	TCs=0 bps		TCs=25 bps		TCs=50 bps	
Panel A: PLS	CER gain (%)	SR	CER gain (%)	SR	CER gain (%)	SR
CDP^{sPCA}	1.4	0.87	1.24	0.86	1.09	0.85
$ECON^{sPCA}$	-0.33	0.79	-0.65	0.76	-0.98	0.74
Panel B: sPCA	CER Gain (%)	SR	CER Gain (%)	SR	CER Gain (%)	SR
CDP^{sPCA}	1.05	0.85	0.95	0.84	0.86	0.83
$ECON^{sPCA}$	-2.9	0.64	-3.49	0.6	-4.09	0.55
Panel C: PLS+sPCA	CER Gain (%)	SR	CER Gain (%)	SR	CER Gain (%)	SR
CDP$^{PLS+sPCA}$	1.73	0.89	1.58	0.88	1.42	0.86
$ECON^{PLS+sPCA}$	-1.54	0.72	-2.13	0.68	-2.72	0.64

Table A16: Economic value results: risk aversion=6

This table reports the annualized CER gains (in %) and annualized Sharpe ratios for a mean-variance investor with a risk-aversion coefficient of six, for predicting future market excess returns by using aggregate predictors based on CDPs and the 14 economic variables in Welch and Goyal (2008) constructed with PLS (CDP^{PLS} & $ECON^{PLS}$) in Panel A, sPCA (CDP^{sPCA} & $ECON^{sPCA}$) in Panel B, and the dynamic combination strategy of PLS and sPCA: ($CDP^{PLS+sPCA}$ & $ECON^{PLS+sPCA}$) in Panel C, relative to historical mean returns. We consider three cases: zero transaction cost and a proportional transaction cost of 25 and 50 basis points per transaction. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021.

	TCs=0 bps		TCs=25 bps		TCs=50 bps	
Panel A: PLS	CER gain (%)	SR	CER gain (%)	SR	CER gain (%)	SR
CDP^{sPCA}	1.59	0.89	1.35	0.86	1.12	0.84
$ECON^{sPCA}$	2.36	0.94	1.82	0.9	1.28	0.86
Panel B: sPCA	CER Gain (%)	SR	CER Gain (%)	SR	CER Gain (%)	SR
CDP^{sPCA}	0.35	0.81	0.13	0.79	-0.09	0.77
$ECON^{sPCA}$	-1.65	0.65	-2.24	0.59	-2.84	0.54
Panel C: PLS+sPCA	CER Gain (%)	SR	CER Gain (%)	SR	CER Gain (%)	SR
CDP$^{PLS+sPCA}$	1.78	0.9	1.41	0.87	1.05	0.84
$ECON^{PLS+sPCA}$	-0.61	0.73	-1.48	0.67	-2.35	0.6

Table A17: Economic value results: risk aversion=7

This table reports the annualized CER gains (in %) and annualized Sharpe ratios for a mean-variance investor with a risk-aversion coefficient of seven, for predicting future market excess returns by using aggregate predictors based on CDPs and the 14 economic variables in Welch and Goyal (2008) constructed with PLS (CDP^{PLS} & $ECON^{PLS}$) in Panel A, sPCA (CDP^{sPCA} & $ECON^{sPCA}$) in Panel B, and the dynamic combination strategy of PLS and sPCA: ($CDP^{PLS+sPCA}$ & $ECON^{PLS+sPCA}$) in Panel C, relative to historical mean returns. We consider three cases: zero transaction cost and a proportional transaction cost of 25 and 50 basis points per transaction. *, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample spans the period from Feb 1994 to Mar 2021.

	TCs=0 bps		TCs=25 bps		TCs=50 bps	
Panel A: PLS	CER gain (%)	SR	CER gain (%)	SR	CER gain (%)	SR
CDP^{sPCA}	1.37	0.89	1.14	0.86	0.9	0.84
$ECON^{sPCA}$	2.67	0.99	2.07	0.94	1.46	0.89
Panel B: sPCA	CER Gain (%)	SR	CER Gain (%)	SR	CER Gain (%)	SR
CDP^{sPCA}	0.46	0.83	0.22	0.81	-0.01	0.78
$ECON^{sPCA}$	-1.44	0.65	-2.02	0.59	-2.6	0.54
Panel C: PLS+sPCA	CER Gain (%)	SR	CER Gain (%)	SR	CER Gain (%)	SR
CDP$^{PLS+sPCA}$	1.66	0.91	1.27	0.87	0.89	0.84
$ECON^{PLS+sPCA}$	-0.33	0.75	-1.24	0.68	-2.14	0.6