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Does economic uncertainty matter in international commodity futures markets?†

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Abstract

This paper examines whether economic uncertainty risk is significantly priced in international commodity futures markets. Contrary to the belief that commodity futures are sensitive to economic uncertainty, our results provide concrete evidence that uncertainty risk is not significantly priced. To explain these results, we examine whether financial intermediaries who are supposed to be marginal investors are not uncertainty averse. We find that the effect of economic uncertainty becomes insignificant after financialization, that is, a large inflow of financial investors, in 2004 and the relation between economic uncertainty and intermediaries' leverage ratio is insignificant. These results suggest that economic uncertainty might not be priced because it is not a significant concern of financial intermediaries.

Classification codes: G10

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† The data that support the findings of this study are available from the corresponding author upon reasonable request.

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1. Introduction

Commodity prices are expected to vary with the business cycle or the economic state. As essential inputs in the production of goods, they can depend on supply and demand, which vary with the economic state. The rapid development and industrialization of emerging countries, especially China, has led to the recent commodity price boom (Kilian, 2009; Tang & Xiong, 2012; Erten & Ocampo, 2013). Specifically, Erten and Ocampo (2013) argue that the rapid increase in commodity prices in the early 2000s was driven by the extraordinary growth of major developing countries, particularly China. Tang and Xiong (2012) also document that the growth of emerging economies has contributed to the change in the price dynamics of commodity futures. Moreover, as hedging instruments or alternative assets for financial investors, commodity prices can also be associated with the economic state. In the literature, commodity futures markets show low correlation with other financial assets, such as stocks and bonds, and commodity futures even show very low correlations across different commodities within commodity futures markets (Erb & Harvey, 2006). Index investment peaked in mid-2008, during the global financial crisis, at no less than $200 billion (Tang & Xiong, 2012), because of hedging and diversification purposes. More importantly, Tang and Xiong (2012) note that the rapid growth of commodity index investment by financial investors since the early 2000s has changed the price dynamics of commodity futures.

This paper explores the pricing effect of economic uncertainty in international commodity futures markets. According to previous studies documenting that commodity prices vary with the economic state, economic uncertainty,[1] which indicates uncertainty about future real economic activity, can be a significant concern for commodity futures market participants and can thus be a priced factor in commodity futures markets. From the perspective of hedgers and commodity producers, uncertainty about the future economic state indicates uncertainty about future demand and they might therefore be willing to hedge this uncertainty risk. The literature on the theoretical models of commodities suggests

[1] More specifically, Jurado et al. (2015.p.1171) define economic uncertainty as "the conditional volatility of a disturbance that in unforecastable from the perspective of economic agents."

that demand shock plays an essential role in determining commodity producers' hedging demand and thus affects expected returns on commodity futures (Gorton et al., 2012; Acharya et al., 2013; Yang, 2013). If the demand shock depends on the future economic state, economic uncertainty about the future economic state would be expected to also be closely associated with the commodity futures risk premium.

On the other hand, from the perspective of speculators or financial investors, since recent studies report that economic uncertainty has a significant relation with stock returns (Bali et al., 2017; Yun et al., 2019), economic uncertainty can be a concern even in commodity futures markets in managing risks of their portfolios. Recent studies on intermediary asset pricing—such as those of Etula (2013), He and Krishnamurthy (2013), and He, Kelly, and Manela (2017; hereafter HKM)—give more weight to the importance of investments by financial investors or speculators who are likely to be financial intermediaries. He and Krishnamurthy (2013) provide a theoretical model where a financial intermediary is a marginal investor, not a household, and the financial intermediary's constraint on equity capital generates the risk premium. HKM empirically examine whether a shock to the equity capital ratio of financial intermediaries (primary dealers) is significantly priced in various asset markets, including commodity futures markets. Adrian, Etula, and Muir (2014; hereafter AEM) also develop a financial intermediary asset pricing model similar to that of He and Krishnamurthy (2013) but, in their model, the financial intermediary has funding constraints, not capital constraints. They measure the tightness of intermediary funding constraints with changes in the leverage ratio of financial intermediaries (broker–dealers) and show that their leverage factor carries a significantly positive premium in the US stock and bond markets.

Our empirical results are in great contrast with the common belief that economic uncertainty significantly affects expected returns on commodity futures. Our empirical results using the uncertainty index of Jurado et al. (2015) provide consistent evidence of the insignificant pricing effects of US economic uncertainty in international commodity futures markets. The results show that US economic uncertainty is not priced in either the US or Chinese commodity futures markets in both the portfolio

and cross-sectional analyses. With respect to longer-term future returns up to one year, the results remain consistently insignificant. We also employ the volatility index as an alternative measure of uncertainty, and revisit the pricing effect of it in both the short-term and the long-term. This robustness test shows the consistent result, which is insignificant pricing effect of uncertainty.

Bali et al. (2017) show that economic uncertainty is negatively priced in the US markets, which could imply that marginal investors in the stock market are uncertainty averse. As the intermediary asset pricing model assumes, if financial intermediaries are marginal investors in asset markets, including both the stock and commodity futures markets, then, along with the empirical findings of Bali et al. (2017), uncertainty can also be expected to be negatively priced in commodity futures markets. However, we find the insignificant pricing effect of economic uncertainty in international commodity futures markets.

Motivated by the literature on the recent increase in financial investors and speculators in commodity futures markets (Tang & Xiong, 2012; Baker, 2014; Hamilton & Wu, 2014) and on intermediary asset pricing (Etula, 2013; He & Krishnamurthy, 2013; HKM), further analyses are conducted to investigate why economic uncertainty is not priced in international commodity futures markets. Specifically, from the view of intermediary asset pricing, our results could imply that financial intermediaries are not uncertainty averse. To examine this more directly, two more analyses are performed. First, the sample period is split into two subperiods, one before financialization (from 1979 to 2004) and one after financialization (from 2005 to 2017), and cross-sectional analysis in each subperiod is then conducted. If recent financialization indicates a large inflow of financial intermediaries and they are uncertainty averse, then a more significant pricing effect of economic uncertainty will be observed, at least in the later subperiod. Second, using the intermediary factors of AEM and HKM, the relation between intermediary factors and economic uncertainty is investigated. If economic uncertainty is not priced because it is not a significant concern of financial intermediaries, then no significant relation should be observed between economic uncertainty and intermediary factors.

First, the subperiod analysis provides partial evidence of the negative uncertainty risk premium in the intermediate term in the first subperiod but, in the more recent period, after financialization, it

finds no evidence of any significant pricing effects of economic uncertainty on the US commodity futures markets. In other words, contrary to expectations, the pricing effect of economic uncertainty became insignificant after the large inflow of financial investors in 2004. These results could indicate that financial intermediaries are not uncertainty averse. A possible explanation is that hedgers rather than financial intermediaries (or speculators) are uncertainty averse, possibly because of the demand shock depending on the future economic state and financialization could thus result in an inflow of investors with a larger capacity for bearing uncertainty. Consequently, the negative premium on uncertainty would become weaker after financialization. Moreover, technological development may have led to the reduction in storage and production costs and thus commodity stockouts have become less costly. If hedgers dislike uncertainty because of possible demand shock, then recent technological developments can also contribute to the dissolution of the uncertainty risk premium in addition to the inflow of financial intermediaries in the recent period.

Second, the economic uncertainty index is not found to be significantly related to the intermediary factors of AEM and HKM, after controlling for macroeconomic variables. From the viewpoint of intermediary asset pricing, an intermediary factor is the only pricing factor or one of two pricing factors—the market factor and the intermediary factor, according to HKM's model—in asset markets, including commodity futures markets, and uncertainty would therefore be a priced factor if it were significantly related to the intermediary factor. In line with our previous findings that economic uncertainty is not priced in commodity futures markets, the results in this subsection suggest that economic uncertainty is not priced because it is not significantly related to the leverage or capital ratio of intermediaries.

This paper contributes to the literature in various ways. First, it improves understanding of the commodity future risk premium. The literature has mainly focused on the relation between macroeconomic news or macroeconomic variables (besides economic uncertainty) and expected commodity futures returns. This paper explores the effect of economic uncertainty on international commodity futures markets for the first time. Gospodinov and Jamali (2018) examine whether monetary

policy uncertainty is priced in the US commodity markets, but they examine commodity spot returns and not commodity futures returns. More importantly, they stress that monetary policy uncertainty and economic uncertainty are different.[2]

Second, this paper also extends the literature on the uncertainty risk premium. Previous studies about the pricing effects of economic uncertainty have mainly focused on stock markets. Bali et al. (2017) document that US economic uncertainty has a negative premium in the US stock market. Using the economic uncertainty measure suggested by Jurado et al. (2015), Bali et al. (2017) estimate each stock's sensitivity to uncertainty and call this sensitivity the uncertainty beta. Stocks with a high uncertainty beta have high returns in a state of high uncertainty, which is favorable to uncertainty-averse investors in managing their risk. Specifically, if investors obtain high returns in an unfavorable state of high uncertainty and can thus hedge their uncertainty risk, then these stocks will have low expected returns. On the other hand, Yun et al. (2019) document that the pricing effect of US economic uncertainty in the Korean stock markets differs from the findings of Bali et al. (2017). They find that stocks highly sensitive to US economic uncertainty—either positively or negatively—have lower future returns due to overpricing on these stocks and this overpricing is closely related to individual investor trading.[3] The pricing effect of economic uncertainty in commodity futures markets, however, has not yet been examined. This paper thus contributes to extending the literature on the uncertainty risk premium to international commodity futures markets.

Third, this paper is closely related to the intermediary asset pricing literature. Though our results are consistent with the argument of Daskalaki et al. (2014), that individual commodity futures returns

[2] Gospodinov and Jamali (2018, Table C1) report that the correlation between their monetary policy uncertainty measure and the economic uncertainty index of Jurado et al. (2015), which is also used in the current paper, is only 0.19.

[3] More specifically, motivated by Hong and Sraer's (2016) model, which assumes that stocks with a high market beta are exposed to greater divergence of opinion, Yun et al. (2019) assume that stocks highly sensitive to economic uncertainty, either positively or negatively, are exposed to greater divergence of opinions and are thus overpriced. This overpricing generates an inverted U–shaped relation between expected returns and the uncertainty beta, since both stocks with either a positively and negatively large uncertainty beta will generate lower future returns. Moreover, they also expect this overpricing to be more prominent when there are high limits to arbitrage and in high-sentiment periods than in low-sentiment periods. They name this hypothesis the speculative beta hypothesis.

are substantially heterogeneous and thus depend on commodity-specific factors rather than common factors, it is still surprising that economic uncertainty is not priced in commodity futures markets. The possible reasons for insignificant results are further investigated from the viewpoint of intermediary asset pricing. This study examines how financial intermediaries manage their capital ratio or leverage ratio in accordance with economic uncertainty. The results show that economic uncertainty is not a significant determinant of their capital ratio (or leverage ratio) and is therefore not priced in commodity futures markets.

Lastly, this paper differs from previous studies in the perspective and comprehensiveness of the sample data. Previous empirical results appear to vary substantially, depending on the set of sample commodities or sample economic variables. For example, Cai et al. (2001) examine how the gold futures markets react to 23 US macroeconomic announcements and find that only four of 23 announcements had a significant effect on the volatility of gold futures prices. Christie-David et al. (2000) also examine the effect of macroeconomic news on silver and gold commodity futures prices and report that their prices show significant responses to only a small subset of the sample news items. Barnhart (1989) and Hess et al. (2008) investigate the effects of US macroeconomic announcements on commodity futures indexes and individual commodity futures, respectively, and report mixed results across news items and across commodities. This paper uses the economic uncertainty index of Jurado et al. (2015) as a proxy for US economic uncertainty, which is a factor-based estimate of US economic uncertainty based on a comprehensive set of macroeconomic variables. By using an aggregated uncertainty index instead of each single macroeconomic variable, one solid result can be provided for the effect of macroeconomic uncertainty on commodity futures markets. Moreover, as opposed to previous studies mainly focused on commodities in specific sectors, commodity indexes, or a small number of individual commodities, we explore a broad set of individual commodity futures contracts in international markets, specifically, 40 US commodity futures and 33 Chinese commodity futures contracts.

The remainder of the paper is organized as follows. Section 2 describes the data and variables. Sections 3 and 4 present the empirical results. Specifically, Section 3.1 examines the relation between economic uncertainty and expected returns by forming portfolios. Section 3.2 reports the results from Fama–MacBeth cross-sectional regressions. . In Section 3.3, we conduct a robustness check with an alternative proxy for uncertainty. Sections 4.1 and 4.2 investigate possible explanations for the empirical results in Section 3 from the perspective of intermediary asset pricing. Lastly, Section 5 concludes the paper.

2. Data and variables

Commodity futures data from US and Chinese markets are obtained from Datastream that comprise daily settlement prices on 40 US commodity futures[4] and 33 Chinese commodity futures contracts. The US commodity futures include commodity futures contracts on feeder cattle, live cattle, corn, dry whey, ethanol, lean hogs, lumber, Class IV milk, non-fat dry milk, frozen pork bellies, crude palm oil, oats, rough rice, soybeans, soybean meal, wheat, cocoa, "C" coffee, Brazilian coffee, cotton no. 2, frozen concentrated orange juice, sugar no. 11, coal, Brent crude oil, light crude oil, heating oil, RBOB gasoline, electricity, high grade copper, gold, palladium, platinum, uranium, silver, natural gas, aluminum, copper, lead, nickel, and zinc. The sample period for the US markets is from January 1979 to December 2017.

The Chinese commodity futures include commodity futures contracts on aluminum, copper, fuel oil, gold, natural rubber, rebar steel, hot-rolled coil, wire rod steel, nickel, silver, zinc, lead, no. 1 soybeans, no. 2 soybeans, corn, corn starch, coke, coking coal, egg, iron ore, linear low-density polyethylene (LLDPE), soybean meal, palm oil, polypropylene, plywood, polyvinyl chloride, soybean oil, cotton no. 1, strong gluten wheat, rapeseed oil, white sugar, pure terephthalic acid, and thermal coal.

[4] Among the 40 US commodity futures, five are futures contracts on aluminum, copper, lead, nickel, and zinc and are listed on the London Metal Exchange (LME). Since the prices are quoted in US dollars, these five commodity futures are included in the set of US commodity futures contracts, following the literature (Novy-Marx, 2012; Asness et al., 2013).

The data for the Chinese markets are available from May 1993, but for the cross-sectional analysis, the sample period is set to start in January 2006, since the number of sample contracts exceeds 10 that month following Kang and Kwon (2017). The beta estimation requires the prior 24 to 60 months, and thus we use the Chinese market data from January 2001 to December 2017. Lastly, exchange data obtained from Bloomberg are used to convert the returns on Chinese commodity futures contracts in local currency to US dollar returns.

As we can see from the list of commodities in two sample markets, the compositions of the two sample markets differ substantially. Whereas the US commodity futures markets include various types of commodities, grains, animals, softs, energy, industrial materials, and precious metals, the Chinese markets are mainly composed of industrial materials, such as steel, copper, and LLDPE. Since the demand for these commodities is more likely to change with the economic state relative to other types of commodities, such as grains or animals, they can be more sensitive to future economic uncertainty or stock market conditions. We expect that investigating two large commodity futures markets with different compositions may provide rich implications to the literature.

To compile the time series of futures returns, the nearest contract is assumed to be held up to the end of the month prior to the maturity month. At the end of that month, the position is rolled over to the second contract nearest to maturity and that contract is held up to the end of the month prior to maturity. This rolling procedure allows problems related to lack of liquidity to be minimized and returns from holding the same contract to be computed, instead of having to switch the contract during the holding month.

To examine the effect of economic uncertainty on commodity futures prices, we use the US economic uncertainty index of Jurado et al. (2015) as a proxy for economic uncertainty. Jurado et al. (2015) provide a factor-based estimate of US economic uncertainty based on a comprehensive set of economic variables.[5] Their model estimates the conditional volatility of the unpredictable component

[5] Specifically, real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, bond and stock market indexes, and foreign exchange measures are used.

of the future value of each series and then aggregates them into a market-wide economic uncertainty index. Previous studies on the effects of macroeconomic news on commodity futures markets report mixed results, especially depending on the choice of the macroeconomic variables (Christie-David et al. 2000; Cai et al., 2001; Roache & Rossi, 2010). Since the uncertainty measure of Jurado et al. (2015) is constructed with a comprehensive set of macroeconomic variables, by using this measure instead of each of the macroeconomic variables, we may provide one solid result for the effect of macroeconomic variables on commodity futures markets.

One-, three-, and 12-month-ahead economic uncertainty indexes (UNC1, UNC3, and UNC12, respectively) can be obtained from Sydney Ludvigson's website.[6] In each month and for each sample stock, the uncertainty beta (β_{UNC}) is estimated from the monthly rolling regression of excess stock returns on UNC over the prior 60 months, following Bali et al. (2017) and Yun et al. (2019). At least 24 monthly observations are required for estimation. In estimating the uncertainty beta, the analysis includes Fama and French's (2015) five factors—market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors—and excess returns on the Standard & Poor's Goldman Sachs Commodity Index (GSCI) as the commodity futures market returns, as follows:

$$R_{\mathrm{t}}^{i} = \alpha^{i} + \beta_{UNC}^{i} UNC_{t} + \beta_{MKT}^{i} MKT_{t} + \beta_{SMB}^{i} SMB_{t} + \beta_{HML}^{i} HML_{t} + \beta_{RMW}^{i} RMW_{t} + \beta_{CMA}^{i} CMA_{t} + \beta_{GSCI}^{i} GSCI_{t} + \varepsilon_{t}^{i} \quad (1)$$

where R_{t}^{i} indicates the excess return on commodity futures *i* in month *t*. We use the Fama–French five factors—MKT, SMB, HML, RMW, and CMA—provided by Kenneth French.[7] The computation of the risk-adjusted return of the β_{UNC}-sorted portfolios also uses the Fama–French five factors and GSCI excess return.

The control variables in the cross-sectional analysis include the stock market beta (β_{MKT}), the commodity futures market beta (β_{GSCI}), the basis (Basis), the return on month *t* - 1 (R(-1)), and the return from month *t* - 6 to *t* - 2 (R(-6,-2)). In each month and for each sample stock, the stock market

[6] See https://www.sydneyludvigson.com.
[7] See http://mba.tuck.dartmouth.edu/ pages/ faculty/ken.french/data_library.html.

beta (β_{MKT}) and commodity futures market beta (β_{GSCI}) are estimated from the monthly rolling regression of excess stock returns on the Fama–French five factors and the GSCI excess returns over the prior 60 months (at least 24 months). The basis is defined as the difference between the logarithms of the spot and futures prices. The price of the nearest futures contract maturing in month T_1 ($F_1(t, T_1)$) is employed as the spot price and the price of the second nearest futures contract maturing in month T_2 ($F_2(t, T_2)$) is employed as the futures price, following Fama and French (1987) and Gorton et al. (2012). Thus, the basis is defined as $Basis = \{log(F_1(t, T_1)) - log(F_2(t, T_2))\}/(T_2 - T_1)$.

3. Uncertainty and expected futures returns

3.1. Portfolio-level analysis

This section first examines the relation between the uncertainty beta and expected returns. In each sample country, the commodity futures are sorted into terciles by their uncertainty betas and the raw excess return, risk-adjusted return, and average uncertainty beta of each tercile are computed. A high-minus-low portfolio is also constructed that buys a high–uncertainty beta portfolio and sells a low–uncertainty beta portfolio and whether the difference in the uncertainty beta generates significant difference in returns is examined. Table I reports the monthly average returns on the uncertainty beta portfolios and their significance.

[Insert Table I here]

Yun et al. (2019) develop two hypotheses on the relation between the uncertainty beta and expected stock returns. First, according to the negative premium hypothesis, future returns on the portfolio would monotonically decrease as the uncertainty beta increases. On the other hand, the speculative beta hypothesis suggests an inverted U–shaped pattern of future returns across uncertainty betas. Table II shows that, in both the US and Chinese commodity futures markets, future returns decrease as the uncertainty beta increases, following the negative premium hypothesis. Specifically, the return on the high–uncertainty beta portfolio is much lower than for the other portfolios. For example,

Panel A of Table II shows that all low– and medium–uncertainty beta portfolios show average returns above 0.10% (0.124–0.211%), whereas high–uncertainty beta portfolios generate only around 0.05% (0.043–0.055%). The low return of the high–uncertainty beta portfolio is more notable in the Chinese markets. For example, Panel B shows that, in the case of long-term uncertainty, the high–uncertainty beta portfolio generates -0.112% of the monthly average return, whereas the low–uncertainty beta portfolio generates 0.018% of it.

Most importantly, however, the return differences between the high– and low–uncertainty beta portfolios are not significant in all cases, although the overall results in Table II show a decreasing pattern across uncertainty beta portfolios, which is consistent with the negative premium hypothesis. The results greatly contrast with previous findings from stock markets. Using the same uncertainty index, Bali et al. (2017) report a significant negative premium on the economic uncertainty risk in the US stock markets and Yun et al. (2019) document that stocks that are highly sensitive, either positively or negatively, to US economic uncertainty tend to be overpriced because of speculative trading in the Korean stock markets. By contrast, our results suggest that US economic uncertainty does not significantly affect returns on commodity futures in the US and Chinese markets either way.

The return difference between the high– and low–uncertainty portfolios in the US markets decreases if other risks are accounted for but, in the case of the Chinese markets, the risk-adjusted returns appear to be greater than the raw excess returns. These differences could imply different risk exposures of the commodities in the two markets that could stem from their different compositions.

Our results are consistent with the argument of Daskalaki et al. (2014), that individual commodity futures returns are very heterogeneous, which means that they seem to depend on commodity-specific factors rather than common factors. However, the uncertainty betas used in sorting the portfolios in Table II are not for the subsequent month over which returns are observed, and thus the question of whether this estimated uncertainty beta is a good proxy for the subsequent month's uncertainty beta can also arise. Following Bali et al. (2017), we examine whether the estimate of the uncertainty beta is sufficiently persistent to assume that it is a good proxy for the uncertainty beta of the subsequent month. Cross-sectional regressions of β_{UNC} are run on the lagged β_{UNC} without and with lagged control

variables (β_{GSCI}, β_{MKT}, Basis, R(-1), and R(-6,-2)). Table III shows the predictive power of β_{UNC} for the n-year-ahead β_{UNC} (n = 1, …, 5) and reports the results without and with lagged control variables.

[Insert Table II here]

Overall, the results in Table II seem to be strong enough to examine the relation between β_{UNC} and the expected return. In both cases, without and with control variables, the results show that β_{UNC} is strongly predictable for up to three years in the US commodity futures markets. In the case of long-term uncertainty (UNC12), the four-year-ahead β_{UNC} also shows a significant relation with the lagged β_{UNC} if no other variables are controlled for (*t*-statistics = 2.30). Compared to the findings of Bali et al. (2017) in the US stock market, the predictable horizon appears to be shorter in the US commodity futures markets but, in the case of n = 1, the values of the coefficients on the lagged β_{UNC} are similar to those in the US stock markets. Specifically, for n = 1, all the coefficients on the lagged β_{UNC} are larger than 0.60 and those in the US stock markets are 0.659 and 0.637 without and with control variables, respectively (see Bali et al., 2017, Table 2). In Panel B of Table II, the Chinese markets also show significant predictive power, especially for the shorter horizon compared to the US markets. In the case of n = 2, only the univariate case shows significant results. For n = 1, the values of the coefficients on the lagged β_{UNC} are comparable to those in the US markets. Except for the multivariate regression case of UNC12, all the coefficients are larger than 0.60 for n = 1. Although the predictable horizon seems to be shorter in the Chinese markets, our results still seem strong enough to assume that the estimate of the uncertainty beta is a good proxy for the uncertainty beta of the subsequent month.

In sum, our results show that the expected return increases monotonically as the uncertainty beta increases but the return difference between the high– and low–uncertainty beta portfolios appears to be insignificant in all cases. Moreover, the results suggest that the uncertainty beta is persistent enough to assume that the estimated uncertainty beta can be used as an appropriate proxy for the future uncertainty beta and, therefore, the insignificant return difference does not seem to be driven by the use of an inappropriate proxy for uncertainty risk.

3.2. Cross-sectional analysis

The portfolio analysis in Section 3.1 has the advantage of being nonparametric but it cannot control for the effects of other variables simultaneously. To thoroughly examine the relation between commodity futures returns and economic uncertainty, a cross-sectional analysis is conducted that controls for other effects. Following Fama and MacBeth (1973), in each month, the following cross-sectional regression is run:

$$R_{t+1}^{i} = \gamma_{0,t} + \gamma_{1,t}\beta_{UNC,t}^{i} + \gamma_{2,t}X_{t}^{i} + \varepsilon_{t+1}^{i} \quad (2)$$

where R_{t+1}^{i} indicates the return on commodity futures i in month t + 1 and $\beta_{UNC,t}^{i}$ indicates the uncertainty beta for stock i in month t. The term X_{t}^{i} indicates a set of contract-specific control variables for commodity futures i in month t (a subset of β_{GSCI}, β_{MKT}, Basis, R(-1), and R(-6,-2)). Then, based on monthly estimates of Equation (2), the time-series averages of the estimates are computed, as well as the Newey–West t-statistics (with lag = 12) to determine their significance. In Table III, Panels A and B show the results for the US and Chinese markets, respectively. In models (1) and (2) ((3) and (4)) of each panel, UNC1 (UNC3) is used to estimate the uncertainty beta. Lastly, in the last two columns (models (5) and (6)), long-term economic uncertainty (UNC12) is used.

[Insert Table III here]

The overall results in Table III are consistent with the portfolio analysis findings in Section 3.1. In the US markets, economic uncertainty does not show any significant relation with commodity futures expected returns. Although the coefficients on the uncertainty betas become more negative if other effects are controlled for, they are still insignificant (t-statistics = -0.68 to -1.23). In the Chinese markets, the univariate models (models (1), (3), and (5)) provide results consistent with these from the portfolio analysis, with a negative relation between the uncertainty beta and the expected return, but the multivariate models (models (2), (4), and (6)) show differences. If other effects are controlled for simultaneously, then the coefficients on the uncertainty betas become positive and are even larger in absolute value than in the univariate cases. For example, model (6) shows that the coefficient on the uncertainty beta has a value of 0.011, with t-statistics = 1.19, whereas model (5) shows that it has a

value of -0.001, with *t*-statistics = -0.08. The positive marginal effect of economic uncertainty in the Chinese markets is rather puzzling but still remains insignificant.

The coefficients on the control variables are generally consistent with the literature. First, the past return variables, R(-1) and R(-6,-2), show substantial differences. The prior month's return, R(-1), shows a positive and highly significant relation with the expected return, indicating strong short-term momentum, while the intermediate-term past return excluding the prior month, R(-6,-2), shows insignificant results. Kang and Kwon (2017) report that the one-month momentum is notably strong relative to longer-term momentums in both the US and Chinese markets. Novy-Marx (2012) also reports that, in US commodity futures markets, momentum strategies based on the return between month t - 6 and month t - 2 generate insignificant returns. The basis also shows a positive relation with the expected return, consistent with the literature (Fama & French, 1987; Miffre & Rallis, 2007; Gorton et al., 2012), whereas this relation is rather weak in the Chinese markets.

Next, whether the pricing effect of economic uncertainty is observed in the longer term is examined. Bali et al. (2017) examine the long-term predictive power of the uncertainty beta in the US stock market and document that the negative premium hypothesis is strongly supported, even in the long term. In the Korean stock market, Yun et al. (2019) also report that the pricing effect of US economic uncertainty appears to be significant for up to 12 months, especially if there are high limits to arbitrage. Moreover, the prior literature on the performance of traditional asset pricing models shows differences across horizons in commodity futures markets. Jagannathan (1985) reports that the consumption capital asset pricing model is rejected over monthly horizons in commodity futures markets, but de Roon and Szymanowska (2010) find the opposite results over quarterly horizons. Thus, the pricing effect of economic uncertainty is worth examining in the longer term.

Model (6) in Table III, which includes all the control variables and the long-term economic uncertainty beta (β_{UNC12}), is used to regress the h-month-ahead returns on the set of explanatory variables for h = 2, …, 12. Table V presents the results of the Fama–MacBeth cross-sectional regressions.

[Insert Table IV here]

The results in Table IV are consistent with those in Table III. For two- to 12-month-ahead returns, the uncertainty betas show insignificant relations with expected returns in both the United States and China. The negative premium for commodity futures market risk (β_{GSCI}) is observed in the longer horizon and is even significant in some cases. The prior month return, R(-1), seems to have weaker relations with longer-term returns, with few exceptions. For example, Panel A of Table IV shows that the coefficients on R(-1) are significant in the cases of h = 10 and 11 and Panel B shows they are significant in the cases of h = 8 and 11. These significant relations with the return about one year ahead could be explained by the supply cycle of commodities. Since the US markets include more commodities with a supply cycle, such as grains, Panel A could show more significant relations between the prior month's return and the 10- and 11-month-ahead returns, which have a gap of almost one year with the prior month's return. Furthermore, the basis exhibits insignificant results for both countries, with only two exceptions, in the cases of h = 2 and 4 in the US markets. These results suggest that the basis has predictive power only for short-term future returns in US commodity futures markets.

To summarize, consistent with the previous subsection, the cross-sectional analysis results show that US economic uncertainty is not priced in either the US or Chinese commodity futures markets. To consider the possibility that economic uncertainty is associated with longer-term future returns, the pricing effect of economic uncertainty on h-month-ahead returns for h = 2, …, 12 is examined, but the results consistently remain insignificant.

3.3.Robustness check

In this section, as a robustness check, we employ the VIX as an alternative proxy for economic uncertainty and examine whether it has a significant impact on commodity futures prices. The VIX is one of the most popular proxies for uncertainty (Bloom, 2009) and according to Bekaert et al. (2013), the VIX and the Jurado et al.'s (2015) uncertainty index may contain different information. Specifically, Bekaert et al. (2013) document that the VIX is largely associated with time-varying risk-aversion rather

than economic uncertainty, but still it is worthy enough to examine the effect of economic uncertainty on commodity futures markets with the VIX as an alternative to the uncertainty index.

We employ the volatility index, VIX, for each of our sample countries, and thus examine the effects of US economic uncertainty and Chinese economic uncertainty, separately. For the US market uncertainty, we use CBOE volatility index and for the Chinese market uncertainty, we use CBOE China ETF volatility index. Due to data availability, the sample periods for the US and Chinese indexes are from January 1990 to December 2017 and from March 2011 to December 2017, respectively. Using these indexes, in each month we compute the change in the VIX (ΔVIX) and estimate each contract's VIX beta, the sensitivity to the VIX, as we estimate the uncertainty beta. Then, we examine the relation between the commodity futures expected return and the economic uncertainty beta by running cross-sectional regressions as in previous sections.

[Insert Table V about here]

Table V shows the results for the Fama-MacBeth cross-sectional regressions. In each panel, models (1) and (2) ((3) and (4)) include the US VIX beta, $\beta_{\Delta USVIX}$ (the Chinese VIX beta, $\beta_{\Delta CHVIX}$) to examine the effects of US (Chinese) economic uncertainty, and models (5) and (6) include both the US and Chinese VIX betas. If we include the Chinese VIX beta in the regression model, the sample period becomes short as the Chinese VIX data span only about 7 years, but we can examine the marginal effect of US and Chinese economic uncertainty on each of the sample markets simultaneously.

Not surprisingly, both panels of Table V show that the US and Chinese VIX betas are not significantly related to the expected returns in the international commodity futures markets. In both panels, no model shows significant coefficients on the VIX betas. The empirical results in Table V are consistent with those in Table III. In other words, our results suggest that our finding, which is the insignificant pricing effect of economic uncertainty in the international commodity futures markets, is

robust to the uncertainty measure. Both the US and Chinese VIX, alternative uncertainty measures, provide consistent results.[8]

Overall, our results provide consistent and robust evidence of the insignificant pricing effects of economic uncertainty in international commodity futures markets, which is unexpected, and a possible reason for this insignificant relation is investigated in the following section.

4. A possible explanation: Intermediaries and uncertainty

Our expectation that uncertainty will be priced in commodity futures markets is closely related to the role of financial intermediaries documented in the literature on intermediary asset pricing (He & Krishnamurthy, 2013; AEM; HKM). He and Krishnamurthy (2013) provide a theoretical model where a financial intermediary is a marginal investor, not a household, and the financial intermediary's constraint on the equity capital generates the risk premium. HKM empirically examine whether a shock to the equity capital ratio of financial intermediaries (primary dealers) is significantly priced in various asset markets, including commodity futures markets. AEM also develop a financial intermediary asset pricing model similar to that of He and Krishnamurthy (2013) but, in their model, the financial intermediary has funding constraints, not capital constraints. They measure the tightness of intermediary funding constraints with changes in the leverage ratio of financial intermediaries (broker–dealers) and show that their leverage factor carries a significantly positive premium in the US stock and bond markets. Bali et al. (2017) show that economic uncertainty is negatively priced in the US markets, which could imply that marginal investors in the stock market are uncertainty averse. As the intermediary asset pricing model assumes, if financial intermediaries are marginal investors in asset markets, including both stock and commodity futures markets, then, along with the empirical findings of Bali et al. (2017), uncertainty is also expected to be negatively priced in commodity futures markets.

[8] In untabulated results, we also examine the pricing effect of economic uncertainty in the longer term with the VIX measures. As in Tables IV, we employ model (6) in Table V and regress the h-month-ahead returns on the set of explanatory variables for h= 2 to 12. We find that the results using the VIX measures show the qualitatively similar results.

This section further investigates a possible reason for the insignificant pricing effect of economic uncertainty in international commodity futures markets. Contrary to expectations, the results in Section 3 consistently show that uncertainty is not significantly priced in international commodity futures markets. From the view of intermediary asset pricing, these results suggest that financial intermediaries might not be uncertainty averse. To examine this more directly, two analyses are performed in this section. First, the sample period is split into two subperiods, one before financialization (1979–2004) and the other after (2005–2017) and the cross-sectional analysis is then revisited for each subperiod. Second, using AEM's capital factor and HKM's leverage factor, the relation between the intermediary factors and economic uncertainty is investigated. In this section, the analysis excludes the Chinese markets, since the Chinese market data cover the period only since 2006 and intermediary data are available only for the US markets.

4.1. Before and after financialization

In the early 2000s, the commodity futures markets experienced a dramatic increase in index investment by financial institutions. For example, Tang and Xiong (2012. p.54) document that "the total value of various commodity index-related instruments purchased by institutional investors increased from an estimated $15 billion in 2003 to at least $200 billion in mid-2008." They also find that this financialization of commodity markets caused changes in the price dynamics of commodities after 2004, such as greatly increased price comovement between various commodities. If financialization indicates a large inflow of financial intermediaries and if these financial intermediaries are uncertainty averse, then uncertainty will have a more negatively significant effect on expected returns after financialization. To examine this, the cross-sectional analysis in Section 3.2 is revisited for two subsample periods, from 1979 to 2004 and from 2005 to 2017.

First, the cross-sectional analysis is performed as for Table IV for each of subsamples. In Table VI, Panels A and B show the results of the Fama–MacBeth regressions from 1979 to 2004 and from 2005 to 2017, respectively.

[Insert Table VI here]

The results in Table VI are in strong contrast to expectations: the uncertainty betas show generally insignificant results and the only significant result is observed in the first subperiod, which is before financialization. The 12-month uncertainty beta appears to be significant at the 10% level after other variables are controlled for (*t*-statistics = -1.68). The negative premium is consistent with the findings of Bali et al. (2017) in US stock markets, indicating that investors are uncertainty averse and, therefore, if they obtain high returns in an unfavorable state of high uncertainty and can thus hedge their uncertainty risk, then these contracts will have low expected returns. However, surprisingly, Table VI shows that no negative premium on uncertainty risk is observed after financialization. Although the uncertainty betas are generally insignificant even before financialization, the coefficients on the uncertainty beta become even positive and much less significant after financialization, contrary to expectations. Our results in Table VI cannot tell whether the difference of the coefficients on uncertainty betas in pre- and post-financialization periods is statistically significant or not, but our main interest in this analysis is whether the uncertainty beta is significantly priced after financialization as there was a large inflow of financial intermediaries after financialization. Table VI shows no evidence of the significant pricing effect even after financilization.

The overall results in Table VI seem to be generally consistent with those of the full sample in Table IV. The stock and commodity futures market betas and intermediate-term past return (R(-6,-2)) also show insignificant results, as in Table IV, and the basis consistently shows significant and positive relations with the expected return in both subperiods, although the magnitudes of the coefficients seem a little smaller after 2004. However, interestingly, the prior month's return, R(-1), shows a large difference between the two subperiods. Panel A shows that R(-1) has significant predictive power for the next month's return, whereas Panel B shows insignificant results. In other words, the short-term momentum (one-month momentum) documented in previous studies (Novy-Marx, 2012; Kang & Kwon, 2017) mainly stems from the period before the financialization of commodity futures markets. These results are noteworthy, since the literature on the trading behaviors of hedgers and speculators in commodity futures markets has consistently reported that speculators and financial traders tend to be

momentum traders whereas hedgers tend to be contrarians (Rouwenhorst & Tang, 2012; Dewally et al., 2013). The results suggest that the profits of financial investors, who are likely to be momentum traders, weakened after the large inflow of financial investment into commodity futures markets in the early 2000s. Along with the weaker effect of economic uncertainty since financialization, these results also call for further research on the structural change of risk premiums for hedgers and speculators (or contrarians and momentum traders) since financialization in the early 2000s.

We also examine the pricing effect of economic uncertainty in the longer term, as in Table V. Using model (6) in Table IV, the h-month-ahead returns are regressed on the set of explanatory variables for h = 2, …, 12. The results are reported in Table A.I in the Appendix. Most of features in Table A.I are consistent with the results in Table V. Partial evidence of the negative uncertainty risk premium is found in the intermediate term, for the four- to six-month-ahead returns but, in the more recent period after financialization, no evidence of significant pricing effects of economic uncertainty on US commodity futures markets is found.

What, then, are possible explanations for these results? As documented at the beginning of Section 4, the overall results could indicate that financial intermediaries are not uncertainty averse. If hedgers, rather than financial intermediaries (or speculators), are uncertainty averse, possibly due to demand shock depending on the future economic state,[9] then financialization could result in the inflow of investors with a larger capacity for bearing uncertainty. Consequently, the negative premium on uncertainty would weaken after financialization. Moreover, technological development may have led to a reduction in storage and production costs and commodity stockouts have thus become less costly. If hedgers dislike uncertainty because of possible demand shock, then recent technological development can also contribute to the dissolution of the uncertainty risk premium in addition to the inflow of financial intermediaries in the recent period. The results could be evidence of the rejection of intermediary asset pricing, which means that financial intermediaries are not marginal investors in commodity futures markets and, therefore, uncertainty is not priced, even though the financial

[9] For example, Acharya et al. (2013) develop a model in which hedgers (commodity producers) are risk averse and speculators are risk neutral.

intermediaries are uncertainty averse. However, since HKM report that the intermediaries' capital factor is significantly priced, even in commodity futures markets, the former explanation, that they are not uncertainty averse, seems more probable than the latter explanation that they are not marginal investors in commodity futures markets. To investigate it, in the next section we further examine whether uncertainty affects financial intermediaries' capital (leverage) ratios.

4.2. Intermediaries' leverage ratio and uncertainty

This section more directly examines whether financial intermediaries are uncertainty averse. Specifically, if financial intermediaries are uncertainty averse, then the intermediary factors capturing intermediaries' leverage ratio will vary with the economic uncertainty index. Although AEM and HKM both assume that financial intermediaries are marginal investors of asset markets, AEM imply the procyclical leverage of financial intermediaries and HKM imply a countercyclical leverage. The purpose of this paper is not to evaluate these two models or determine which factor truly captures the status of intermediaries. Therefore, we employ both AEM's capital factor and HKM's leverage factor and investigate the relation between these factors and economic uncertainty. If a state of high uncertainty is an undesirable or bad state for financial intermediaries, then their leverage will be low, according to AEM's argument, or their capital ratio will be low, according to HKM's argument. As Bali et al. (2017) document a negative premium on uncertainty and AEM and HKM note a positive premium on their leverage and capital factors, respectively, a negative relation between uncertainty and the intermediary factors seems reasonable.

To examine this, the following time-series regression is performed:[10]

[10] The contemporaneous relation between the intermediary factors and the economic uncertainty index is examined rather than the predictive relation between the intermediary factors and the lagged value of uncertainty because both the intermediary factors and economic uncertainty are considered predictors of future returns in the literature (AEM; Bali et al., 2017; HKM). We also examine whether the lagged value of the economic uncertainty index has a significant relation with the intermediary factors but find insignificant results only for the univariate regressions.

$$Intermediary_t = \delta_0 + \delta_1 UNC_t + \delta_2 \Delta VIX_t + \delta_3 TED_t + \delta_4 DEF_t + \delta_5 TERM_t + \varepsilon_t \quad (3)$$

where $Intermediary_t$ indicates HKM's capital ratio factor or AEM's leverage factor in month t, UNC_t is one of the uncertainty indexes with different horizons (UNC1, UNC3, and UNC12), and the other variables are control variables, that is, change in the volatility index (ΔVIX_t), the spread between the three-month Treasury bill and the eurodollar, or TED spread (TED_t), the default spread (DEF_t), and the term spread ($TERM_t$). Specifically, HKM's capital ratio factor is a shock to the aggregate capital ratio divided by the lagged capital ratio and the factor data set is provided by Manela.[11] AEM's leverage factor is based on the book values of the total financial assets and liabilities of broker–dealers. Using aggregate quarterly data on the levels of total financial assets and liabilities of security broker–dealers provided by the Federal Reserve (*Flow of Funds*), the seasonally adjusted log change of broker–dealer leverage is computed (see AEM's equation (5)). To maintain the monthly frequency, a quarterly value is assigned to three months within each quarter. The CBOE volatility index (VIX) is used for the volatility index.[12] In addition to the volatility index, three macroeconomic variables are included that could affect the leverage ratio of financial intermediaries (Ang et al., 2011). The analysis includes the TED spread, which is a proxy for the aggregate cost of short-term borrowing for large financial institutions; the term spread, which is the difference between the 10-year Treasury bond yield and the yield on three-month T-bills; and the default spread, which is the difference between Moody's BAA and AAA bond yields. The data for these macroeconomic variables are obtained from the Federal Reserve Bank of St. Louis.

[Insert Table VII here]

In Table VII, Panel A shows the correlations among the variables used in Equation (3). It shows that the correlation between the AEM and HKM factors is substantially low, at 0.019. This result is consistent with HKM's findings. HKM explain that this differences stem from using information from the different intermediary sectors—AEM use the information of broker–dealers and HKM use the

[11] See http://apps.olin.wustl.edu/faculty/manela/data.html.

[12] The VIX data set spans the period from January 1990 to December 2017 and, therefore, this analysis restricts the sample period to starting in 1990.

information of primary dealers—and differences between book and market values. Moreover, Ang et al. (2011) report that these two intermediary sectors move in opposite directions, especially after a negative fundamental shock (e.g., during a crisis when constraints are binding).

More importantly, however, these two factors show similar correlations with economic uncertainty. Regardless of the uncertainty horizons, the economic uncertainty index appears to be negatively correlated with the intermediary factors, even though the correlations are rather weak, around -10%. Not surprisingly, the economic uncertainty index is more closely associated with the macroeconomic variables, TED, DEF, and TERM, rather than the intermediary factors. It appears to be positively related to TED and DEF and negatively related to TERM. It is especially highly correlated with default risk (DEF). The correlations range from 0.726 and 0.727.

This analysis includes the change in the volatility index (ΔVIX) as market volatility, and this is also one of the most popular proxies for uncertainty (Bloom, 2009). However, Bekaert et al. (2013) note that the VIX and the uncertainty index of Jurado et al. (2015) could contain different information. Specifically, Bekaert et al. (2013) document that the VIX is largely associated with time-varying risk aversion rather than economic uncertainty. Consistent with these studies, Panel A of Table VII also suggests that the uncertainty index (UNC) and the change of the VIX (ΔVIX) are qualitatively different from each other. The correlations between the UNC values and ΔVIX are very weak, ranging from 0.025 to 0.032, and ΔVIX appears to be much less correlated to macroeconomic variables compared to the UNC values. These results seem to be consistent with the explanation of Bekaert et al. (2013) that the VIX and the economic uncertainty index capture different information. Therefore, ΔVIX is included to control for the effect of market volatility or the stock market state rather than as an alternative proxy for economic uncertainty.

Panels B and C of Table VII report the estimated results of Equation (3) for the HKM and AEM factors, respectively. In Panel B, the univariate regression models show that the coefficients on UNCs are marginally significant (*t*-statistics = -1.75 to -1.84) but, in the multivariate models, the coefficients on UNC becomes insignificant (*t*-statistics = -0.91 to -1.04). The results for the AEM factor in Panel C are similar to those in Panel B but statistically even weaker. The univariate regressions show negative

but insignificant coefficients on the UNC values and even become positive as other variables are controlled for. Overall, the results in Panel C show an insignificant relation between the economic uncertainty index and AEM's leverage factor.

HKM examine the differences in the empirical performance of two factors, their capital factor and AEM's leverage factor, and find that the leverage factor has limited success only in the stock and bond markets, whereas the capital factor is uniformly and significantly priced in various asset markets. Specifically, HKM find that the capital factor is positively priced in commodity futures markets, with *t*-statistics = 1.90 (Table V), whereas AEM's leverage factor has a positive but insignificant relation (*t*-statistics = 0.60 in Table VII) with expected returns in commodity futures markets. The results in Panels B and C of Table VII show that the uncertainty index has a slightly more significant correlation with the HKM factor, but the coefficient is still only marginally significant. Moreover, the coefficients on the uncertainty index for the HKM factor even become insignificant after other macroeconomic variables are controlled for. From the perspective of intermediary asset pricing, the intermediary factor is the only pricing factor or one of two—the market factor and the intermediary factor, according to HKM's model—in asset markets, including commodity futures markets, and uncertainty is therefore a priced factor if it is significantly related to the intermediary factor. In line with our previous findings that economic uncertainty is not priced in commodity futures markets, the results in this section suggest that it is not priced because it is not significantly related to the leverage or capital ratio of intermediaries.

4.3. Discussion

In Section 4, as a possible reason for the insignificant pricing effect of uncertainty revealed in Section 3, we hypothesize that intermediaries who are supposed to be marginal investors would not be uncertainty averse and empirically investigate the relation between uncertainty and intermediaries. However, in the point of view of intermediary asset pricing, intermediaries are marginal investors in markets regardless of the type of the assets – either stocks or commodity futures – and thus the question

of why the empirical results from the stock (Bali et al., 2017) and commodity futures markets are so different is still unanswered.

We find some clues from motivation of HKM's study in the spirit of intermediary asset pricing. Specifically, HKM document,

"*… most intermediary-based asset pricing models are founded on the limits-to-arbitrage paradigm, in which sophisticated financial intermediaries play a central and dominant role in some asset classes (e.g., derivatives contracts or OTC markets) that are too sophisticated for most household investors. In fact, as we acknowledge below, equity is the asset class where we least expect good performance by the pricing kernel of primary dealers*."

Commodity futures is one of the asset classes that are sophisticated compared to other traditional financial assets and thus as HKM also highlight, the commodity futures market would be the one in which intermediaries would play a dominant role.

Though Bali et al. (2017) do not analyze any relation between the pricing effect of uncertainty and the investor's trading behavior, Yun et al. (2019) provide the evidence that the pricing effect of uncertainty in the Korean equity market is mainly driven by individual investors. In particular, they reveal some differences in the pricing effect of uncertainty in the Korean and the US stock markets and so suggest that uncertainty may affect markets (prices) in a different way depending on composition of investors in the markets. Combining this empirical evidence with the argument of HKM, we expect that it is also possible that the significant pricing effect of uncertainty in the US stock market can be driven by investors other than intermediaries. Up to our best knowledge, this paper is first to examine the relation between economic uncertainty and intermediaries – whether intermediaries are uncertainty averse and how economic uncertainty affects their decisions – and thus we remain this issue for future research.

5. Conclusion

This paper explores the pricing effect of economic uncertainty in international commodity futures markets for the first time in the literature. The pricing effect of economic uncertainty in commodity futures markets has not yet been investigated, despite its importance. This paper provides consistent evidence that, contrary to common belief, economic uncertainty is not significantly priced in international commodity futures markets.

Whether economic uncertainty is a priced risk factor in commodity futures markets is a very important question in various aspects and is, indeed, not a trivial question. Despite strong belief in the relation between the economic variable and commodity (futures) prices, the empirical results continue to cast doubt on it. Previous empirical studies report weak or insignificant relations between the releases of macroeconomic news and commodity (futures) prices. Basistha and Kurov (2015) examine the effect of monetary policy surprises on energy commodity prices and find a significant impact at an intraday frequency, but the accumulated responses over several days after the announcement are insignificant. Gospodinov and Jamali (2018) examine the effect of monetary policy uncertainty on commodity spot prices but find that it is not significantly priced in the cross section of individual commodity prices. More importantly, Daskalaki et al. (2014) examine whether there exist common factors in the cross section of individual commodity futures returns and find that individual commodity futures returns are substantially heterogeneous, which means that they depend on commodity-specific factors rather than common factors. Gospodinov and Jamali (2018) also note that the insignificant pricing effect of monetary policy uncertainty is not surprising, given the findings of Daskalaki et al. (2014).

Our results are consistent with the argument of Daskalaki et al. (2014), but it is still surprising that economic uncertainty is not priced in commodity futures markets. Possible reasons for the insignificant results from the viewpoint of intermediary asset pricing are examined and show that economic uncertainty is not a significant determinant of intermediaries' leverage ratio and is thus not priced in commodity futures markets. The relation between (economic) uncertainty and the leverage management of financial intermediaries has not yet been examined, to the best of our knowledge, and

this paper is the first to document how financial intermediaries manage their leverage or capital ratio in accordance with economic uncertainty. Since recent studies on financial intermediaries stress their role in asset markets, further research on the link between uncertainty and financial intermediaries is desirable.

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Table I. Uncertainty beta-sorted portfolios

This table shows the monthly average returns on portfolios sorted by the uncertainty betas. Panels A and B present the results for commodity futures in the US and Chinese markets, respectively. The terms UNC1, UNC3, and UNC3 indicate the uncertainty measures used to estimate the uncertainty betas that are the one-, three-, and 12-month-ahead economic uncertainty indexes, respectively. In computing the risk-adjusted return on a portfolio, the raw excess return of the portfolio is regressed on the Fama–French five factors and the GSCI excess return. The sample periods for the US and Chinese markets are from January 1979 to December 2017 and from January 2006 to December 2017, respectively. The column with the uncertainty beta heading shows the average uncertainty beta of each portfolio. The numbers in parentheses are Newey–West (1987) adjusted *t*-statistics.

Panel A: US markets									
Uncertainty beta portfolio	UNC1			UNC3			UNC12		
	Raw excess	Risk-adjusted	Uncertainty beta	Raw excess	Risk-adjusted	Uncertainty beta	Raw excess	Risk-adjusted	Uncertainty beta
Low	0.170%	0.020%	-0.345	0.138%	-0.018%	-0.337	0.211%	0.041%	-0.534
	(0.85)	(0.10)	(-50.32)	(0.70)	(-0.09)	(-46.56)	(1.11)	(0.21)	(-43.45)
Med	0.176%	0.030%	-0.045	0.193%	0.055%	-0.049	0.124%	-0.039%	-0.084
	(0.96)	(0.16)	(-9.16)	(1.06)	(0.30)	(-10.40)	(0.67)	(-0.21)	(-11.55)
High	0.043%	-0.094%	0.254	0.055%	-0.086%	0.251	0.052%	-0.046%	0.383
	(0.21)	(-0.45)	(22.31)	(0.27)	(-0.41)	(20.22)	(0.26)	(-0.22)	(21.86)
High - Low	-0.127%	-0.114%	0.599	-0.083%	-0.067%	0.588	-0.159%	-0.087%	0.917
	(-0.57)	(-0.48)	(40.08)	(-0.38)	(-0.29)	(35.58)	(-0.74)	(-0.38)	(37.98)
Panel B: Chinese markets									
Uncertainty beta portfolio	UNC1			UNC3			UNC12		
	Raw excess	Risk-adjusted	Uncertainty beta	Raw excess	Risk-adjusted	Uncertainty beta	Raw excess	Risk-adjusted	Uncertainty beta
Low	0.110%	0.173%	-0.171	0.008%	0.049%	-0.168	0.018%	-0.048%	-0.307
	(0.33)	(0.50)	(-14.40)	(0.03)	(0.15)	(-14.80)	(0.05)	(-0.13)	(-13.93)
Med	-0.096%	-0.214%	0.025	0.019%	-0.068%	0.019	-0.035%	-0.053%	0.023
	(-0.27)	(-0.62)	(3.48)	(0.05)	(-0.19)	(2.64)	(-0.11)	(-0.17)	(1.56)
High	-0.150%	-0.292%	0.223	-0.164%	-0.320%	0.210	-0.112%	-0.252%	0.349
	(-0.35)	(-0.67)	(15.79)	(-0.39)	(-0.74)	(15.45)	(-0.25)	(-0.55)	(14.97)

High - Low	-0.261%	-0.465%	0.394	-0.172%	-0.369%	0.378	-0.130%	-0.204%	0.656
	(-0.74)	(-1.27)	(22.59)	(-0.49)	(-1.03)	(22.79)	(-0.36)	(-0.53)	(24.69)

Table II. Persistency of uncertainty betas

This table shows the predictive power of β_{UNC} for the n-year-ahead β_{UNC} (n = 1, …, 5). Panels A and B present the results for commodity futures in the US and Chinese markets, respectively. The terms UNC1, UNC3, and UNC12 indicate the uncertainty measures used to estimate the uncertainty betas that are the one-, three-, and 12-month-ahead economic uncertainty indexes, respectively. Cross-sectional regressions of β_{UNC} are run on the lagged β_{UNC} without and with lagged control variables. The control variables include the betas of the GSCI return (β_{GSCI}) and the stock market excess return (β_{MKT}), the return on month *t* - 1 (R(-1)), the return from months *t* - 6 to *t* - 2 (R(-6,-2)), and the basis. The results without and with control variables are reported in the columns with headings univariate and multivariate, respectively. The sample periods for the US and Chinese markets are from January 1979 to December 2017 and from January 2006 to December 2017, respectively. The numbers in parentheses are Newey–West (1987) adjusted *t*-statistics.

n-Year-ahead beta	UNC1		UNC3		UNC12	
	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate
Panel A: US markets						
n = 1	0.691	0.674	0.688	0.663	0.653	0.640
	(11.74)	(12.79)	(12.09)	(12.56)	(12.20)	(12.47)
n = 2	0.443	0.403	0.438	0.400	0.416	0.394
	(5.79)	(6.06)	(6.50)	(6.64)	(7.01)	(6.40)
n = 3	0.250	0.215	0.252	0.218	0.276	0.247
	(2.74)	(2.91)	(3.03)	(3.38)	(3.79)	(3.57)
n = 4	0.109	0.082	0.127	0.103	0.165	0.120
	(1.31)	(1.13)	(1.65)	(1.69)	(2.30)	(1.67)
n = 5	0.036	0.069	0.070	0.118	0.100	0.132
	(0.37)	(0.80)	(0.74)	(1.43)	(1.07)	(1.47)
Panel B. Chinese markets						
n = 1	0.672	0.640	0.664	0.627	0.630	0.579
	(9.22)	(10.02)	(8.92)	(9.38)	(7.66)	(6.86)
n = 2	0.272	0.097	0.263	0.179	0.218	0.110
	(2.62)	(0.75)	(2.59)	(1.76)	(1.96)	(0.97)
n = 3	-0.081	0.434	-0.094	-0.097	-0.111	-0.238
	(-0.53)	(0.67)	(-0.58)	(-0.44)	(-0.69)	(-1.31)
n = 4	-0.290	0.282	-0.332	-0.206	-0.351	-0.389
	(-1.65)	(0.42)	(-1.68)	(-0.73)	(-1.73)	(-1.84)
n = 5	-0.425	0.397	-0.451	-0.260	-0.444	-0.476
	(-2.41)	(0.47)	(-2.30)	(-0.80)	(-2.37)	(-2.08)

Table III. Fama–MacBeth regression

This table shows the results of Fama–MacBeth cross-sectional regressions. Panels A and B present the results for commodity futures in the US and Chinese markets, respectively. The table reports the estimated coefficients on the betas of UNC1 (β_{UNC1}), UNC3 (β_{UNC3}), UNC12 (β_{UNC12}), the GSCI return (β_{GSCI}), and the stock market excess return (β_{MKT}), as well as coefficients on the return on month *t* - 1 (R(-1)), the return from months *t* - 6 to *t* - 2 (R(-6,-2)), and the basis. The sample periods for the US and Chinese markets are from January 1979 to December 2017 and from January 2006 to December 2017, respectively. The numbers in parentheses are Newey–West (1987) adjusted *t*-statistics.

Panel A: US markets						
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.001	0.000	0.001	0.000	0.001	0.000
	(0.49)	(-0.15)	(0.49)	(-0.17)	(0.46)	(-0.25)
β_{UNC1}	-0.001	-0.004				
	(-0.15)	(-0.68)				
β_{UNC3}			-0.001	-0.005		
			(-0.23)	(-0.82)		
β_{UNC12}					-0.003	-0.005
					(-0.66)	(-1.23)
β_{GSCI}		-0.003		-0.003		-0.003
		(-0.70)		(-0.74)		(-0.65)
β_{MKT}		0.235		0.263		0.253
		(0.85)		(0.95)		(0.93)
R(-1)		0.051		0.051		0.055
		(2.73)		(2.74)		(2.82)
R(-6,-2)		0.006		0.006		0.006
		(0.84)		(0.86)		(0.88)
Basis		0.187		0.190		0.198
		(5.18)		(5.20)		(5.31)
Panel B: Chinese markets						
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.000	-0.005	0.000	-0.001	0.000	-0.003
	(0.06)	(-0.98)	(-0.01)	(-0.12)	(-0.07)	(-0.76)
β_{UNC1}	-0.003	0.020				
	(-0.29)	(1.12)				
β_{UNC3}			-0.003	0.038		
			(-0.22)	(1.57)		
β_{UNC12}					-0.001	0.011
					(-0.08)	(1.19)
β_{GSCI}		-0.024		-0.022		-0.018
		(-1.97)		(-1.82)		(-1.67)
β_{MKT}		-1.121		0.372		-0.198
		(-1.11)		(0.56)		(-0.43)
R(-1)		0.173		0.209		0.167
		(2.54)		(2.18)		(2.64)
R(-6,-2)		-0.007		-0.004		-0.003

	(-0.29)	(-0.19)	(-0.14)
Basis	0.740	0.473	0.592
	(1.62)	(1.56)	(1.65)

Table IV. Long-term predictive regression

This table shows the Fama–MacBeth regression with the two- to 12-month-ahead (h = 2, …, 12) returns. Panels A and B present the results for commodity futures in the US and Chinese markets, respectively. The table reports the estimated coefficients on the betas of UNC1 (β_{UNC1}), UNC3 (β_{UNC3}), UNC12 (β_{UNC12}), the GSCI return (β_{GSCI}), and the stock market excess return (β_{MKT}), as well as coefficients on the return on month *t* - 1 (R(-1)), the return from months *t* - 6 to *t* - 2 (R(-6,-2)), and the basis. The sample periods for the US and Chinese markets are from January 1979 to December 2017 and from January 2006 to December 2017, respectively. The numbers in parentheses are Newey–West (1987) adjusted *t*-statistics.

	h = 2	h = 3	h = 4	h = 5	h = 6	h = 7	h = 8	h = 9	h = 10	h = 11	h = 12
						Panel A: US markets					
Intercept	0.001	-0.001	0.001	0.001	0.002	0.001	0.002	0.002	0.003	0.003	0.003
	(0.69)	(-0.23)	(0.45)	(0.55)	(0.94)	(0.42)	(0.97)	(0.95)	(1.11)	(1.31)	(1.41)
β_{UNC12}	-0.005	-0.005	-0.004	-0.006	-0.007	-0.003	-0.003	-0.003	-0.002	-0.002	0.000
	(-1.33)	(-1.13)	(-0.94)	(-1.31)	(-1.45)	(-0.83)	(-0.66)	(-0.73)	(-0.38)	(-0.57)	(0.12)
β_{GSCI}	-0.004	-0.007	-0.009	-0.007	-0.001	-0.004	-0.002	-0.004	-0.002	-0.008	-0.011
	(-0.86)	(-1.62)	(-1.92)	(-1.48)	(-0.26)	(-0.89)	(-0.37)	(-0.84)	(-0.43)	(-1.62)	(-2.46)
β_{MKT}	0.402	0.404	0.245	0.042	0.063	0.183	0.150	0.178	0.161	0.272	0.354
	(1.41)	(1.49)	(0.82)	(0.15)	(0.25)	(0.85)	(0.60)	(0.70)	(0.77)	(1.08)	(1.48)
R(-1)	0.034	0.030	0.007	-0.008	0.015	0.006	0.002	0.014	0.058	0.064	0.000
	(1.95)	(1.62)	(0.39)	(-0.48)	(1.01)	(0.35)	(0.15)	(0.77)	(3.25)	(3.77)	(0.02)
R(-6,-2)	-0.003	0.000	-0.005	0.013	0.021	0.025	0.024	0.019	-0.001	-0.006	-0.019
	(-0.34)	(0.03)	(-0.65)	(1.86)	(2.85)	(3.12)	(2.57)	(2.06)	(-0.19)	(-0.79)	(-2.10)
Basis	0.105	0.069	0.108	-0.021	0.006	0.033	0.007	-0.011	0.002	-0.032	0.057
	(2.80)	(1.62)	(2.30)	(-0.41)	(0.12)	(0.77)	(0.13)	(-0.22)	(0.05)	(-0.69)	(1.69)
						Panel B: Chinese markets					
Intercept	-0.004	0.000	-0.001	-0.003	-0.005	0.002	0.004	0.000	0.000	0.002	-0.002
	(-0.68)	(-0.07)	(-0.22)	(-0.62)	(-0.89)	(0.45)	(0.85)	(-0.04)	(-0.13)	(0.66)	(-0.52)
β_{UNC12}	0.011	-0.006	-0.004	0.002	-0.004	0.004	0.005	0.006	-0.004	0.001	0.000
	(1.09)	(-0.60)	(-0.52)	(0.23)	(-0.44)	(0.53)	(1.00)	(0.67)	(-0.43)	(0.12)	(-0.04)
β_{GSCI}	-0.022	-0.018	0.004	-0.016	-0.004	-0.008	-0.026	-0.030	-0.004	-0.043	-0.034

	(-1.56)	(-1.84)	(0.20)	(-1.11)	(-0.25)	(-0.63)	(-2.72)	(-3.09)	(-0.35)	(-3.88)	(-2.69)
β_{MKT}	0.038	0.068	0.977	0.056	-0.201	0.176	0.487	-0.126	0.622	0.095	0.174
	(0.08)	(0.11)	(1.67)	(0.11)	(-0.48)	(0.35)	(1.13)	(-0.26)	(1.17)	(0.18)	(0.29)
R(-1)	0.020	0.182	0.026	-0.092	-0.028	0.010	0.083	-0.104	0.092	0.165	-0.088
	(0.35)	(1.30)	(0.41)	(-1.41)	(-0.30)	(0.17)	(2.07)	(-1.83)	(1.89)	(2.90)	(-1.39)
R(-6,-2)	-0.030	0.000	0.009	0.030	0.019	0.026	-0.003	0.000	0.016	-0.001	-0.009
	(-0.97)	(0.01)	(0.57)	(1.65)	(0.74)	(1.42)	(-0.16)	(0.01)	(0.81)	(-0.04)	(-0.45)
Basis	0.612	-0.425	0.300	0.427	0.750	0.759	-0.262	0.270	-0.384	-0.632	0.249
	(1.26)	(-1.00)	(0.85)	(1.20)	(1.11)	(1.50)	(-0.82)	(1.47)	(-0.94)	(-1.08)	(0.57)

Table V. Fama-MacBeth regression using VIX

This table shows the results of Fama-MacBeth cross-sectional regressions. Panels A and B present the results for commodity futures in the US and Chinese markets, respectively. The table reports the estimated coefficients on the betas of the change in the US VIX ($\beta_{\Delta USVIX}$), the change in the Chinese VIX ($\beta_{\Delta CHVIX}$), the GSCI return (β_{GSCI}), and the stock market excess return (β_{MKT}) as well as coefficients on the return on month t-1 (R(-1)), the return from month t-6 to t-2 (R(-6,-2)), and the basis. The numbers in parentheses are Newey–West (1987) adjusted *t*-statistics.

Panel A. US						
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.003	0.001	0.000	-0.008	-0.001	-0.008
	(1.24)	(0.46)	-(0.08)	-(1.63)	-(0.25)	-(1.50)
$\beta_{\Delta USVIX}$	0.308	0.288			0.014	-0.445
	(1.03)	(0.96)			(0.02)	-(0.86)
$\beta_{\Delta CHVIX}$			-0.442	-0.360	-0.215	-0.111
			-(0.73)	-(0.82)	-(0.33)	-(0.24)
β_{GSCI}		-0.002		0.005		0.003
		-(0.37)		(0.38)		(0.27)
β_{MKT}		0.326		0.907		0.806
		(1.07)		(1.52)		(1.46)
R(-1)		0.045		-0.017		-0.007
		(2.07)		-(0.34)		-(0.15)
R(-6,-2)		-0.001		0.003		0.014
		-(0.10)		(0.30)		(1.47)
Basis		0.210		0.197		0.177
		(4.51)		(2.31)		(1.83)
Panel B. China						
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.001	0.003	0.002	0.003	0.000	0.001
	(0.26)	(0.46)	(0.32)	(0.60)	(0.04)	(0.27)
$\beta_{\Delta USVIX}$	0.090	-0.181			0.877	1.265
	(0.23)	-(0.24)			(0.94)	(1.62)
$\beta_{\Delta CHVIX}$			0.197	-0.105	-0.780	-1.325
			(0.33)	-(0.13)	-(0.62)	-(0.86)
β_{GSCI}		-0.003		-0.020		-0.020
		-(0.35)		-(1.71)		-(1.57)
β_{MKT}		-1.116		0.170		-0.126
		-(0.97)		(0.22)		-(0.15)
R(-1)		0.108		0.030		0.025
		(1.06)		(0.93)		(0.79)
R(-6,-2)		0.054		0.034		0.035
		(1.72)		(1.39)		(1.36)
Basis		1.264		0.133		0.116
		(1.44)		(2.64)		(2.25)

Table VI. Fama–MacBeth regression in subperiods

This table shows the results of Fama–MacBeth cross-sectional regressions in the US commodity futures markets. Panels A and B present the results for the subperiods from 1979 to 2004 and from 2005 to 2017, respectively. The table reports the estimated coefficients on the betas of UNC1 (β_{UNC1}), UNC3 (β_{UNC3}), UNC12 (β_{UNC12}), the GSCI return (β_{GSCI}), and the stock market excess return (β_{MKT}), as well as coefficients on the return on month *t* - 1 (R(-1)), the return from months *t* - 6 to *t* - 2 (R(-6,-2)), and the basis. The numbers in parentheses are Newey–West (1987) adjusted *t*-statistics.

Panel A: From 1979 to 2004						
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.16)	(-0.05)	(-0.16)	(-0.05)	(-0.15)	(-0.08)
β_{UNC1}	-0.004	-0.008				
	(-0.79)	(-1.25)				
β_{UNC3}			-0.005	-0.009		
			(-0.89)	(-1.34)		
β_{UNC12}					-0.006	-0.007
					(-1.29)	(-1.68)
β_{GSCI}		-0.006		-0.006		-0.005
		(-1.21)		(-1.20)		(-0.93)
β_{MKT}		0.171		0.219		0.201
		(0.45)		(0.57)		(0.54)
R(-1)		0.057		0.059		0.063
		(2.63)		(2.67)		(2.77)
R(-6,-2)		0.006		0.006		0.006
		(0.68)		(0.68)		(0.66)
Basis		0.193		0.196		0.203
		(3.93)		(3.92)		(3.97)
Panel B: From 2005 to 2017						
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.003	-0.001	0.003	-0.001	0.003	-0.001
	(0.84)	(-0.15)	(0.84)	(-0.18)	(0.77)	(-0.26)
β_{UNC1}	0.006	0.002				
	(0.47)	(0.16)				
β_{UNC3}			0.006	0.001		
			(0.50)	(0.08)		
β_{UNC12}					0.003	-0.001
					(0.47)	(-0.07)
β_{GSCI}		0.003		0.003		0.001
		(0.44)		(0.35)		(0.13)
β_{MKT}		0.354		0.343		0.350
		(1.05)		(1.00)		(1.02)
R(-1)		0.039		0.038		0.038
		(1.18)		(1.15)		(1.15)
R(-6,-2)		0.005		0.005		0.006
		(0.48)		(0.54)		(0.62)

Basis	0.174	0.179	0.188
	(3.62)	(3.71)	(3.84)

Table VII. Intermediaries and uncertainty

In this table, Panel A shows the correlations among the variables used in Equation (3) and Panels B and C show the estimated results of Equation (3) for HKM's capital factor and AEM's leverage factor, respectively. Shown are HKM's and AEM's capital and leverage factors for financial intermediaries, respectively, and UNC1, UNC3, and UNC12 for the one-, three-, and 12-month-ahead economic uncertainty indexes, respectively. The other variables are control variables, that is, change in the volatility index (ΔVIX), the spread between the three-month Treasury bill and the eurodollar (TED), the default spread (DEF), and the term spread ($TERM$). The numbers in parentheses are Newey–West (1987) adjusted *t*-statistics.

Panel A: Correlations

	UNC3	UNC12	ΔVIX	HKM	AEM	TED	DEF	TERM
UNC1	0.996	0.958	0.032	-0.095	-0.124	0.301	0.726	-0.134
UNC3	1	0.976	0.028	-0.095	-0.132	0.328	0.727	-0.157
UNC12		1	0.025	-0.090	-0.107	0.419	0.726	-0.155
ΔVIX			1	-0.522	0.126	0.115	-0.086	-0.038
HKM				1	0.019	-0.163	0.013	0.058
AEM					1	-0.114	-0.042	0.056
TED						1	0.296	-0.203
DEF							1	0.257

Panel B: Simultaneous regressions for HKM's factor

	UNC1		UNC3		UNC12	
Intercept	0.047	0.049	0.052	0.059	0.080	0.108
	(1.86)	(1.62)	(1.87)	(1.57)	(1.91)	(1.30)
UNC	-0.070	-0.050	-0.063	-0.055	-0.085	-0.102
	(-1.75)	(-0.91)	(-1.77)	(-1.00)	(-1.84)	(-1.04)
ΔVIX		-0.008		-0.008		-0.008
		(-6.36)		(-6.35)		(-6.36)
TED		-0.008		-0.007		-0.006
		(-0.64)		(-0.59)		(-0.47)
DEF		-0.007		-0.006		-0.006

		(-0.40)		(-0.32)		(-0.33)
TERM		-0.001		-0.001		-0.001
		(-0.33)		(-0.39)		(-0.38)
Panel C: Simultaneous regressions for AEM's factor						
	UNC1		UNC3		UNC12	
Intercept	0.086	0.015	0.100	0.003	0.129	-0.120
	(1.53)	(0.36)	(1.61)	(0.06)	(1.33)	(-1.09)
UNC	-0.117	0.114	-0.114	0.109	-0.129	0.233
	(-1.35)	(1.42)	(-1.44)	(1.38)	(-1.22)	(1.73)
ΔVIX		0.002		0.002		0.002
		(2.08)		(2.09)		(2.08)
TED		-0.032		-0.032		-0.036
		(-2.05)		(-2.07)		(-2.33)
DEF		-0.072		-0.073		-0.076
		(-4.03)		(-3.88)		(-4.01)
TERM		-0.002		-0.002		-0.002
		(-0.61)		(-0.54)		(-0.51)

Table AI. Long-term predictive regression by subperiod

This table shows the results of Fama–MacBeth regression with the two- to 12-month-ahead (h = 2, …, 12) returns in the US commodity futures markets. Panels A and B present the results for the subperiods from 1979 to 2004 and from 2005 to 2017, respectively. The table reports the estimated coefficients on the betas of UNC1 (β_{UNC1}), UNC3 (β_{UNC3}), UNC12 (β_{UNC12}), the GSCI return (β_{GSCI}), and the stock market excess return (β_{MKT}), as well as the coefficients on the return on month *t* - 1 (R(-1)), the return from months *t* - 6 to *t* - 2 (R(-6,-2)), and the basis. The numbers in parentheses are Newey–West (1987) adjusted *t*-statistics.

	h = 2	h = 3	h = 4	h = 5	h = 6	h = 7	h = 8	h = 9	h = 10	h = 11	h = 12
					Panel A: From 1979 to 2004						
Intercept	0.001	0.000	0.001	0.001	0.001	0.000	0.002	0.002	0.003	0.004	0.004
	(0.41)	(-0.01)	(0.40)	(0.35)	(0.59)	(-0.09)	(0.79)	(0.99)	(1.34)	(1.75)	(1.75)
β_{UNC12}	-0.005	-0.007	-0.010	-0.010	-0.011	-0.007	-0.003	-0.003	-0.002	-0.004	-0.001
	(-1.31)	(-1.62)	(-2.26)	(-2.01)	(-2.29)	(-1.46)	(-0.70)	(-0.64)	(-0.30)	(-0.82)	(-0.12)
β_{GSCI}	-0.004	-0.007	-0.011	-0.004	-0.003	-0.003	0.000	-0.002	-0.001	-0.011	-0.009
	(-0.61)	(-1.22)	(-1.86)	(-0.72)	(-0.43)	(-0.54)	(0.02)	(-0.33)	(-0.08)	(-1.70)	(-1.94)
β_{MKT}	0.455	0.434	0.286	0.070	-0.024	0.104	0.022	0.012	-0.032	0.112	0.302
	(1.20)	(1.14)	(0.73)	(0.20)	(-0.07)	(0.38)	(0.07)	(0.04)	(-0.12)	(0.36)	(0.94)
R(-1)	0.029	0.024	0.001	-0.008	0.026	0.017	0.005	0.026	0.057	0.056	-0.008
	(1.33)	(0.94)	(0.05)	(-0.36)	(1.27)	(0.81)	(0.23)	(1.09)	(2.69)	(2.37)	(-0.37)
R(-6,-2)	-0.003	0.001	0.005	0.021	0.025	0.028	0.021	0.020	-0.003	-0.008	-0.025
	(-0.23)	(0.12)	(0.51)	(2.46)	(2.71)	(2.57)	(1.67)	(1.48)	(-0.32)	(-0.79)	(-2.05)
Basis	0.081	0.039	0.124	-0.030	-0.012	0.031	-0.018	-0.049	-0.037	-0.036	0.017
	(1.73)	(0.76)	(2.35)	(-0.43)	(-0.19)	(0.52)	(-0.22)	(-0.74)	(-0.53)	(-0.58)	(0.44)
					Panel B: From 2005 to 2017						
Intercept	0.002	-0.002	0.001	0.002	0.004	0.003	0.003	0.002	0.001	0.001	0.001
	(0.55)	(-0.29)	(0.26)	(0.42)	(0.73)	(0.62)	(0.60)	(0.43)	(0.27)	(0.24)	(0.18)
β_{UNC12}	-0.005	0.000	0.008	0.003	0.003	0.005	-0.002	-0.003	-0.002	0.001	0.003
	(-0.61)	(-0.03)	(1.11)	(0.41)	(0.37)	(0.69)	(-0.21)	(-0.37)	(-0.23)	(0.12)	(0.36)
β_{GSCI}	-0.005	-0.007	-0.006	-0.012	0.001	-0.006	-0.006	-0.008	-0.006	-0.004	-0.015
	(-0.65)	(-1.17)	(-0.71)	(-1.61)	(0.19)	(-0.80)	(-0.68)	(-1.06)	(-0.63)	(-0.42)	(-1.59)

β_{MKT}	0.296	0.344	0.161	-0.014	0.236	0.339	0.406	0.511	0.546	0.591	0.458
	(0.74)	(1.22)	(0.38)	(-0.03)	(0.60)	(1.04)	(1.35)	(1.43)	(1.78)	(1.59)	(1.53)
R(-1)	0.045	0.042	0.019	-0.009	-0.007	-0.017	-0.002	-0.009	0.060	0.079	0.018
	(1.52)	(1.95)	(0.74)	(-0.31)	(-0.44)	(-0.79)	(-0.10)	(-0.34)	(1.91)	(4.50)	(0.83)
R(-6,-2)	-0.003	-0.001	-0.025	-0.002	0.014	0.019	0.028	0.018	0.002	-0.002	-0.008
	(-0.30)	(-0.16)	(-2.31)	(-0.19)	(1.11)	(1.93)	(2.82)	(2.21)	(0.26)	(-0.20)	(-0.69)
Basis	0.154	0.130	0.075	-0.003	0.040	0.036	0.057	0.066	0.082	-0.025	0.136
	(2.55)	(1.75)	(0.82)	(-0.04)	(0.64)	(0.79)	(1.05)	(0.83)	(0.94)	(-0.38)	(2.51)