

# CURRENCY RISK IN THE LONG RUN

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*The views expressed here are those of the authors and not those of the Hong Kong Monetary Authority.*

## INTRODUCTION

Banks' have increased their **appetite for sovereign debt**

- To satisfy post-crisis liquidity requirements as government bonds are easy and quick to sell during times of distress,
- Government bonds carry very little risk-weight and banks are not required to raise much extra capital to hold them.

Pension funds and insurers are **another major source of demand**

- Centrally-cleared derivatives more expensive after post-crisis rules.
- These players buy long-term bonds to hedge interest rate risk.

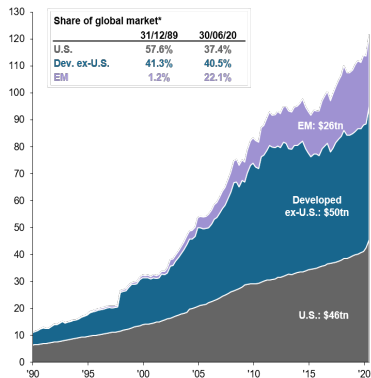
**Carry strategy** implemented with long-term bonds in foreign currencies

- Returns fall with bond maturity (Lustig, Stathopoulos & Verdelhan, 2020),
- Positive post-crisis returns (Andrews, Croce, Colacito & Gavazzoni, 2021).

# FACTS ABOUT THE BOND MARKET



(a) Source: Financial Times (2017)



(b) Source: JP Morgan Asset Management (2020)

## MOTIVATION

Modern financial economics has little to say about the risk of long-term bonds

- Investors would naturally hold short-term bonds and **demand a premium to hold long-term bonds** (e.g., Keynes, 1930; Hicks, 1946),
- Investors who value the **stability of income** require a premium to go short, not to go long (Modigliani & Sutch, 1966),
- Viceira & Wang (2016) find that the **portfolio risk** of a bond portfolio declines with the investment horizon.

Investment decisions are based upon return forecasts

- Investors' knowledge is limited (true parameters are unknown),
- Observable predictors deliver an imperfect proxy for future returns,
- Predictive variability of returns differ from true variability, thus affecting the perceived risk across investment horizons.

# SUMMARY OF THE PAPER

## What we do ...

- We take the perspective of a US investor and estimate the **predictive variance** of a bond-based currency strategy over long-horizons,
- We estimate a **predictive system with imperfect predictability** using long-span data akin to Pastor & Stambaugh (2009),
- We decompose the predictive variance into **five components** using **closed-form expressions** by building on and extending Pastor & Stambaugh (2012).

## What we find (so far) ...

- Long-horizon **predictive variance** is upward sloping for all G10 countries,
- **Future uncertainty** about conditional returns is a critical driver,
- **Real interest rate differential** and **real exchange rate returns** play a major role for the predictive variance of our excess returns.

## A SIMPLE CURRENCY STRATEGY

A **global strategy** from the perspective of a US investor

- She borrows at the **short-term interest rate** at home,
- She invests in the **constant-maturity bond** abroad
- Akin to Andrews, Croce, Colacito & Gavazzoni (2021).

The **excess return** of this strategy can be then written as

$$rx_{t+1} = y_{t+1}^* + \Delta s_{t+1} - i_t$$

- $rx_t$  → one-month excess return in dollars,
- $y_t^*$  → one-month return on the foreign bond,
- $\Delta s_t$  → one-month nominal exchange rate return,
- $i_t$  → one-month deposit rate in dollars.

## A SIMPLE CURRENCY STRATEGY

We work with long-span data (more than 200 years)

- Different monetary policy and exchange rate regimes.

We can equivalently rewrite our excess return in **real terms** as

$$rx_{t+1} = \underbrace{y_{t+1}^* - i_t^*}_{\substack{\text{foreign bond} \\ \text{excess return} \\ r_{1,t+1}}} + \underbrace{(i_t^* - \rho_{t+1}^*) - (i_t - \rho_{t+1})}_{\substack{\text{real interest} \\ \text{rate differential} \\ r_{2,t+1}}} + \underbrace{\Delta s_{t+1} + \rho_{t+1}^* - \rho_{t+1}}_{\substack{\text{real exchange} \\ \text{rate return} \\ r_{3,t+1}}}$$

- $i_t^*$  → one-month deposit rate in foreign currency,
- $\rho_t$  → one-month US inflation rate,
- $\rho_t^*$  → one-month foreign inflation rate.

## IMPERFECT PREDICTABILITY

Each return component, for  $s = \{1, 2, 3\}$ , can be described as

$$r_{s,t+1} = \mu_{s,t} + u_{s,t+1}$$

- $\mu_{s,t}$  → expected return conditional on all information at time  $t$ ,
- $u_{s,t+1}$  → unexpected return with zero mean and constant variance.

We model the **expected return** as Pastor & Stambaugh (2009)

$$\mu_{s,t} = a_s + b_s x_{s,t} + \pi_{s,t}$$

- $x_{s,t}$  → observable predictor,
- $\pi_{s,t}$  → unobservable predictor with zero-mean.

The **true expected return** captures more information than we observe

- An observable predictor is likely to be **imperfect**,
- We may understate the **variance of future returns**.



## PREDICTIVE VARIANCE

Define the  $k$ -period return between times  $T + 1$  and  $T + k$  as

$$r_{s,T}^k = \sum_{\ell=1}^k r_{s,T+\ell}$$

- $r_{s,T+\ell}$  → one-period return between  $T + \ell - 1$  and  $T + \ell$ .

We study the predictive variance of  $rx$  over long horizons as

$$\text{Var}(rx_T^k | D_T) = \sum_{i=1}^3 \sum_{j=1}^3 \text{Cov}(r_{i,T}^k, r_{j,T}^k | D_T)$$

- $D_T$  → information set used for predictability at time  $T$ .

$D_T$  includes the full history of returns and observable predictors

- No information about the unobservable predictor  $\pi$  and parameters  $\phi$  governing the relationship between returns and predictors.

## PREDICTIVE VARIANCE

Each predictive covariance can be decomposed as

$$\begin{aligned} \text{Cov}(r_{i,T}^k, r_{j,T}^k | D_T) &= \underbrace{\mathbb{E}[\text{Cov}(r_{i,T}^k, r_{j,T}^k | \pi_T, \phi, D_T) | D_T]}_{\text{Expectation of the conditional covariance of the } k\text{-period returns}} \\ &+ \underbrace{\text{Cov}[\mathbb{E}(r_{i,T}^k | \pi_T, \phi, D_T), \mathbb{E}(r_{j,T}^k | \pi_T, \phi, D_T) | D_T]}_{\text{Covariance of the conditional expected } k\text{-period returns}} \end{aligned}$$

An investor who knows  $\pi_T$  and  $\phi$  only cares the conditional covariance

- An investor who ignores  $\pi$  and  $\phi$  also cares about its expectation,
- She also accounts for the covariance of the conditional expected returns,
- The perceived variance can be higher, in absolute terms, at long horizons.

## PREDICTIVE SYSTEM

Consider the following predictive system

$$r_{t+1} = a + bx_t + \pi_t + u_{t+1}$$

$$x_{t+1} = \theta + \gamma x_t + v_{t+1}$$

$$\pi_{t+1} = \delta \pi_t + \eta_{t+1}$$

- $r_t \rightarrow$  vector of returns,
- $x_t \rightarrow$  vector of observable predictors modeled as an AR(1) process,
- $\pi_t \rightarrow$  vector of unobservable predictors as a driftless AR(1) process.

The role of **observable predictors**

- capture the direct/indirect effects of monetary policy decisions.

The role of **unobservable predictors**

- capture aspects of monetary policy **not contained in bond yields**,
- structural variations due to **different exchange rate regimes**.

## DECOMPOSITION

The **expectation of the conditional covariance** consists of three terms

- *i.i.d.* uncertainty [▶ details](#)
- mean reversion [▶ details](#)
- future conditional mean uncertainty [▶ details](#)

The **covariance of the conditional expectation** consists of two terms

- current conditional mean uncertainty [▶ details](#)
- estimation risk [▶ details](#)

We then calculate the covariance ratio of each component

$$CR(k) = \frac{\text{Cov}(r_{i,T}^k, r_{j,T}^k | D_T)}{k \text{Cov}(r_{i,T}^1, r_{j,T}^1 | D_T)}$$

to determine the shape of the long-horizon covariance curve.

# LONG-SPAN DATA

## Sample and Source

- Monthly observations from January 1800 to June 2017,
- Unbalanced dataset from Global Financial Data.

## Dataset

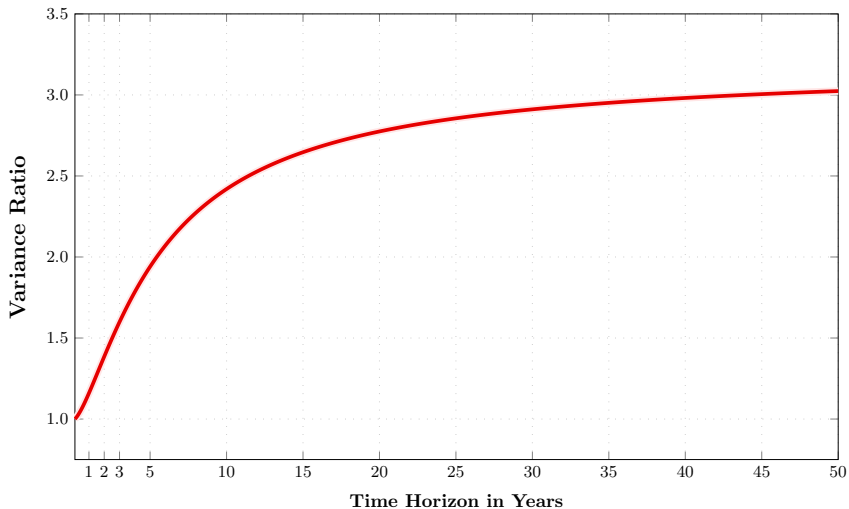
- **Bond returns:** 10-year constant-maturity treasury bond returns,
- **Deposit rates:** 3-month Treasury bills,
- **Exchange rates:** bilateral US dollar spot exchange rates,
- **Price indices:** year-on-year inflation rates

## G-10 Countries

- Australia, Canada, Germany/Euro Area, Japan, New Zealand, Norway, Sweden, Switzerland, UK, and US.

▶  $r_t$  ▶  $x_t$  ▶  $\pi_t$

## TOTAL PREDICTIVE VARIANCE: US/UK

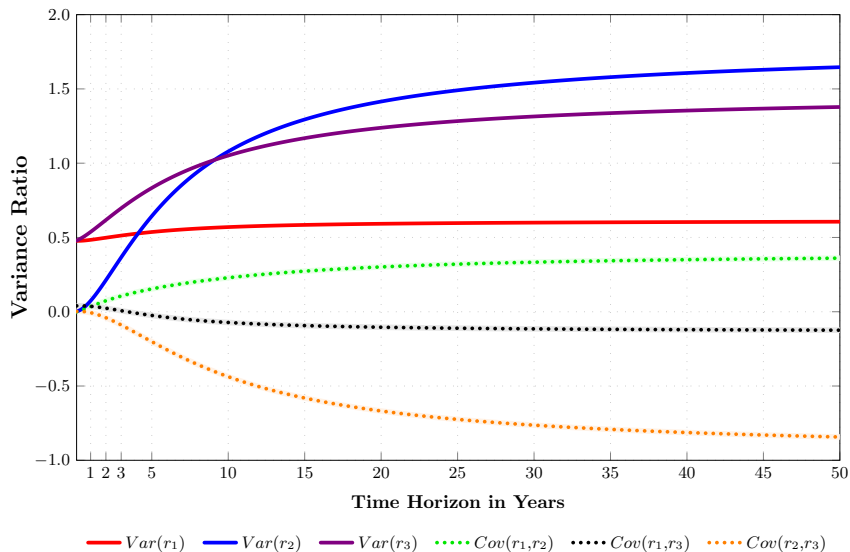


Global

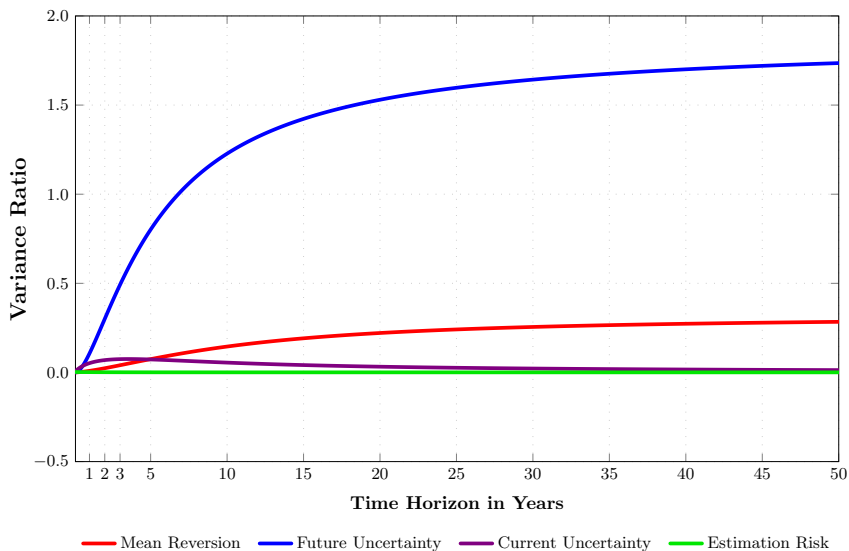
Germany

Japan

# PREDICTIVE VARIANCE DECOMPOSITION: US/UK

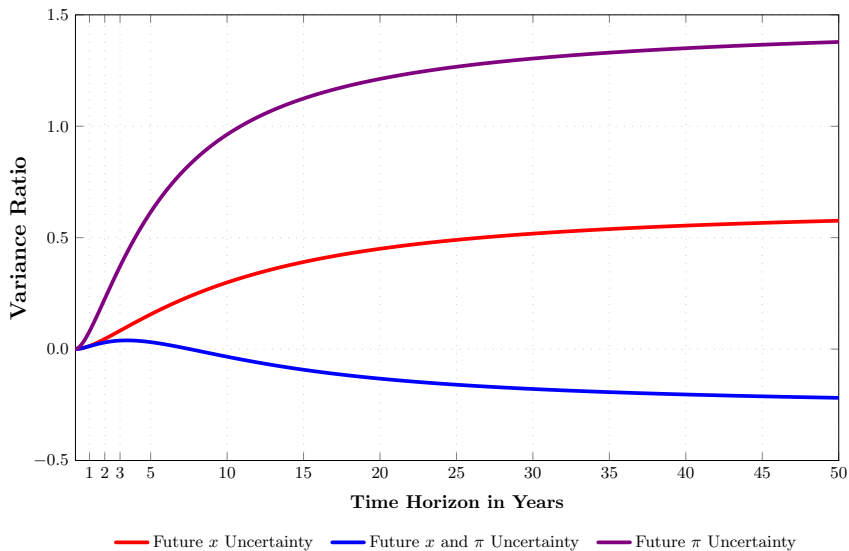


## PREDICTIVE VARIANCE DECOMPOSITION: US/UK





## FUTURE (CONDITIONAL MEAN) UNCERTAINTY: US/UK



# TO SUM UP

## Main message

- The predictive variance of a bond-based currency strategy can be **large**,
- The largest portion of variance risk is related to **real interest rate differential** and **real exchange rate returns**.
- **Uncertainty about future returns** is the dominant component of the predictive variance.

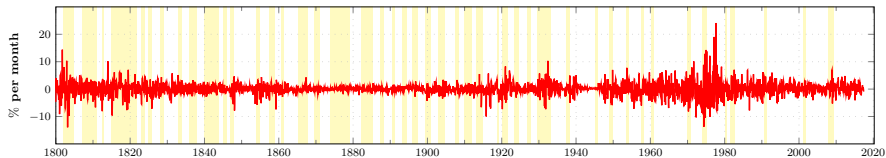
## Ongoing research

- Robustness across different priors, samples, and predictors,
- A model to understand the asset pricing and asset allocation implication.
- Working on the narrative of our results (e.g., monetary policy events).

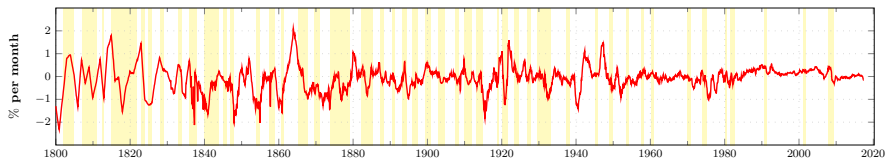
# Appendix

# DEPENDENT VARIABLES: UK

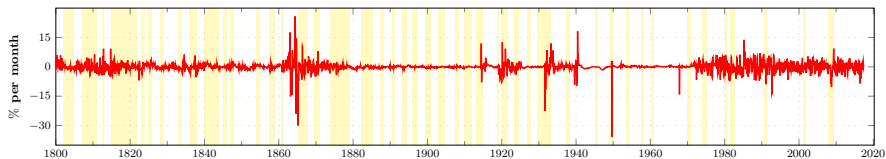
## UK Bond Excess Return



## UK/US Real Interest Rate Differential



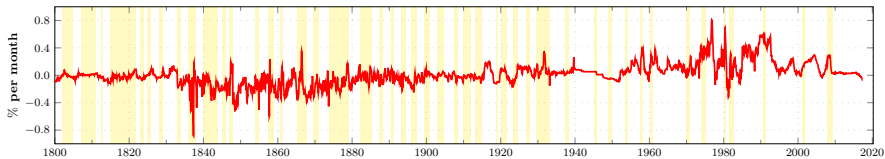
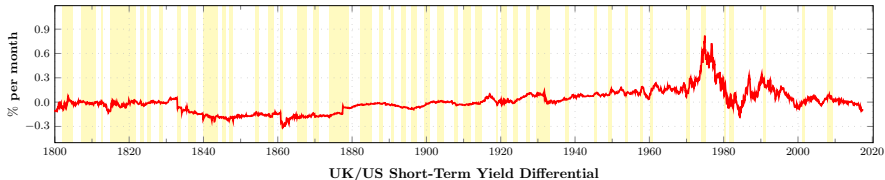
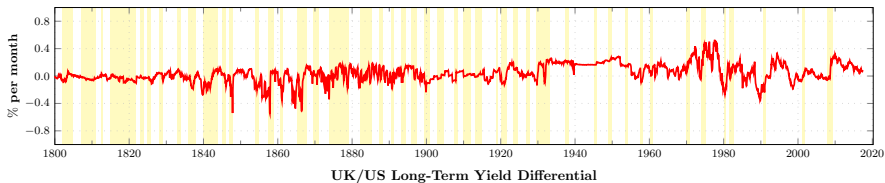
## UK/US Real Exchange Rate Return



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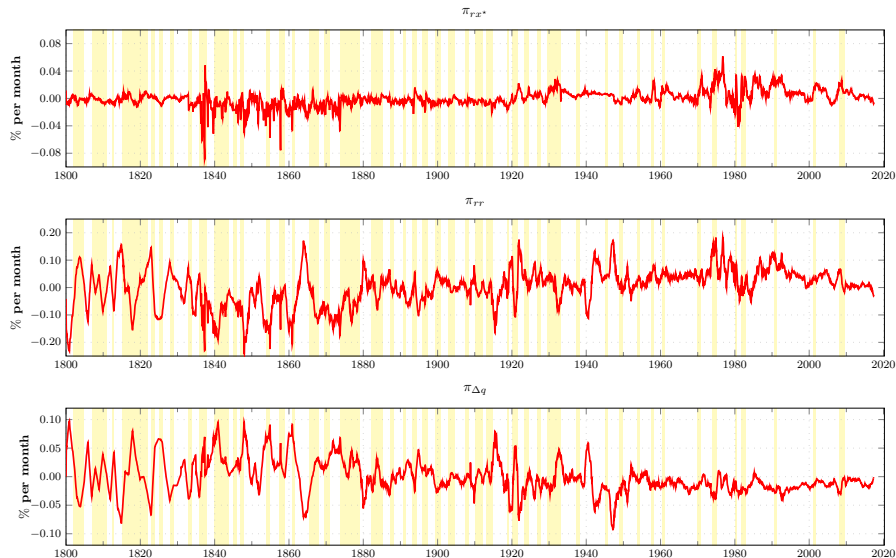
# OBSERVABLE PREDICTORS: UK

UK Term Spread



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# UNOBSERVABLE PREDICTORS: UK



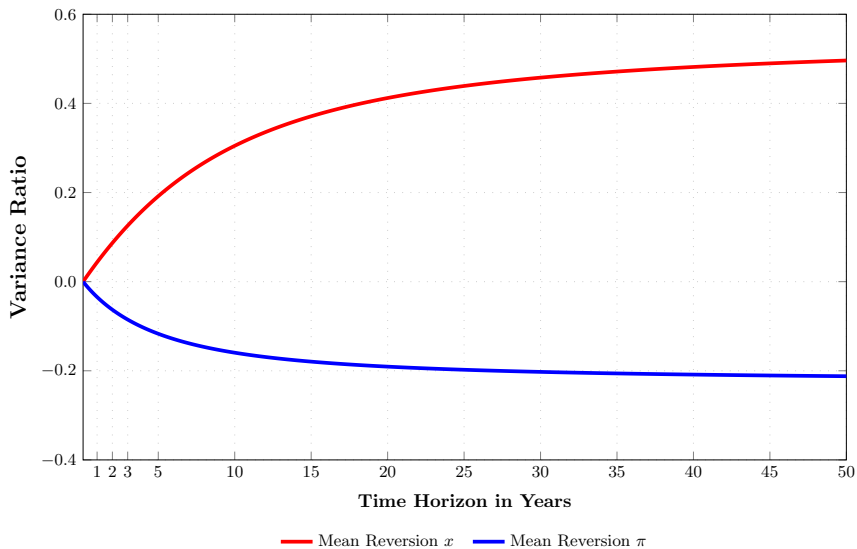
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## MEAN REVERSION DECOMPOSITION: US/UK



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# COMPONENTS

- The *i.i.d. uncertainty* is defined as

$$\mathbb{E} [k\sigma_{u_i}\sigma_{u_j}\rho_{u_i u_j} \mid D_T]$$

- ✓ it captures the well-known feature of *iid* returns,
- ✓ it is proportional to  $k$  (i.e., per-period covariance is constant),
- ✓ it reflects parameter uncertainty,
- ✓ it reduces to  $E[k\sigma_{u_i}^2 \mid D_T]$  when  $i = j$ .

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# COMPONENTS

- The **mean reversion** is defined as

$$\underbrace{\mathbb{E} (k\sigma_{u_i}\sigma_{u_j} [b_i\bar{d}_i\rho_{v_i u_j}A_i(k, \gamma) + b_j\bar{d}_j\rho_{u_i v_j}A_j(k, \gamma)] \mid D_T)}_{\text{mean reversion } x} +$$
$$\underbrace{\mathbb{E} (k\sigma_{u_i}\sigma_{u_j} [\bar{e}_i\rho_{\eta_i u_j}A_i(k, \delta) + \bar{e}_j\rho_{u_i \eta_j}A_j(k, \delta)] \mid D_T)}_{\text{mean reversion } \pi}$$

- Key properties**

- ✓ **mean reversion**  $x$  vanishes with no observable predictors, i.e.,  $b_s = 0$ ,
- ✓ **mean reversion**  $\pi$  disappears with perfect observable predictors, i.e.,  $\sigma_{\pi_s}^2 \rightarrow 0$  which directly impact  $\bar{e}_s$ .

▶  $\bar{d}_s$

▶  $\bar{e}_s$

▶  $A(k, \phi)$

◀ Go back

# COMPONENTS

- The **future conditional mean uncertainty** is defined as

$$\underbrace{\mathbb{E} [k\sigma_{u_i}\sigma_{u_j} b_i b_j \bar{d}_i \bar{d}_j \rho_{v_i v_j} B_{ij}(k, \gamma, \gamma) \mid D_T]}_{\text{future } x \text{ uncertainty}} +$$
$$\underbrace{\mathbb{E} (k\sigma_{u_i}\sigma_{u_j} [b_i \bar{d}_i \bar{e}_j \rho_{v_i \eta_j} B_{ij}(k, \gamma, \delta) + b_j \bar{e}_i \bar{d}_j \rho_{\eta_i v_j} B_{ij}(k, \delta, \gamma)] \mid D_T)}_{\text{future } x \text{ and } \pi \text{ joint uncertainty}} +$$
$$\underbrace{\mathbb{E} [k\sigma_{u_i}\sigma_{u_j} \bar{e}_i \bar{e}_j \rho_{\eta_i \eta_j} B_{ij}(k, \delta, \delta) \mid D_T]}_{\text{future } \pi \text{ uncertainty}}$$

- Key properties**

- ✓ **future  $x$  uncertainty** and **future  $x$  and  $\pi$  joint uncertainty** vanish with no observable predictors, i.e.,  $b_s = 0$ ,
- ✓ **future  $\pi$  uncertainty** and **future  $x$  and  $\pi$  joint uncertainty** disappears with perfect observable predictors, i.e.,  $\sigma_{\pi_s}^2 \rightarrow 0$ .

▶  $B_{ij}(k, \phi, \psi)$

◀ Go back

# COMPONENTS

- The **current conditional mean uncertainty** is defined as

$$\mathbb{E} \left[ \frac{1 - \delta_i^k}{1 - \delta_i} \frac{1 - \delta_j^k}{1 - \delta_j} q_{ij, T} \mid D_T \right]$$

where  $q_{ij, T} = \text{Cov}(\pi_{i, T}, \pi_{j, T} \mid \boldsymbol{\phi}, D_T)$

- **Key properties**

✓ This term vanishes with perfect observable predictors ( $\sigma_{\pi_s}^2 \rightarrow 0$ ).

▶  $q_{ij, T}$

◀ Go back

## COMPONENTS

- The **estimation risk** is defined as

$$\text{Cov} \left[ kE_{r_i} + \frac{1 - \gamma_i^k}{1 - \gamma_i} (a_i + b_i x_{i,T} - E_{r_i}) + \frac{1 - \delta_i^k}{1 - \delta_i} c_{i,T}, \right. \\ \left. kE_{r_j} + \frac{1 - \gamma_j^k}{1 - \gamma_j} (a_j + b_j x_{j,T} - E_{r_j}) + \frac{1 - \delta_j^k}{1 - \delta_j} c_{j,T} \mid D_T \right]$$

✓  $E_{r_s}$  ( $s = i, j$ ) are the unconditional mean returns

▶  $E_{r_s}$   $c_{s,T}$

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## COMPONENTS

$$\bar{d}_s = \left( \frac{1 + \gamma_s}{1 - \gamma_s} \frac{R_s^2}{1 - R_s^2} \frac{\sigma_{x_s}^2}{\sigma_{r_s}^2 - \sigma_{u_s}^2} \right)^{1/2} .$$

$$R_s^2 = \frac{b_s^2 \sigma_{x_s}^2 + \sigma_{\pi_s}^2 + 2b_s \sigma_{x_s} \pi_s}{\sigma_{r_s}^2}$$

◀ Go back

## COMPONENTS

$$\bar{e}_s = \left( \frac{1 + \delta_s}{1 - \delta_s} \frac{R_s^2}{1 - R_s^2} \frac{\sigma_{\pi_s}^2}{\sigma_{r_s}^2 - \sigma_{u_s}^2} \right)^{1/2}$$

$$R_s^2 = \frac{b_s^2 \sigma_{x_s}^2 + \sigma_{\pi_s}^2 + 2b_s \sigma_{x_s} \pi_s}{\sigma_{r_s}^2}$$

◀ Go back



## COMPONENTS

$$A_s(k, \phi) = 1 + \frac{1}{k} \left( -1 - \phi_s \frac{1 - \phi_s^{k-1}}{1 - \phi_s} \right)$$

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## COMPONENTS

$$B_{ij}(k, \phi, \psi) = 1 + \frac{1}{k} \left( -1 - \phi_i \frac{1 - \phi_i^{k-1}}{1 - \phi_i} - \psi_j \frac{1 - \psi_j^{k-1}}{1 - \psi_j} + \right. \\ \left. + \phi_i \psi_j \frac{1 - \phi_i^{k-1} \psi_j^{k-1}}{1 - \phi_i \psi_j} \right)$$

◀ Go back

# COMPONENTS

◀ Go back

$$q_{ij, T} = \text{Cov}(\pi_{i, T}, \pi_{j, T} \mid \boldsymbol{\phi}, D_T)$$

## COMPONENTS

$$E_{r_s} = a_s + b_s \frac{\theta_s}{1 - \gamma_s}$$

$$c_{s,T} = E(\pi_{s,T} \mid \boldsymbol{\phi}, D_T)$$

◀ Go back