Mispricing and Uncertainty in International Markets

Mirela Sandulescu and Paul Schneider

Discussion by Rohit Allena
Goizueta Business School
Emory University

March 05, 2021

EMORY
GOIZUETA
BUSINESS
SCHOOL

Essence of the paper

Explaining asset prices using SDF is a fundamental problem in finance

Essence of the paper

Explaining asset prices using SDF is a fundamental problem in finance

$$E_t(M_{t+1}R_{i,t+1}) = 0 \ \forall i, \text{ where } M_{t+1} \text{ is the SDF} \tag{1}$$

Essence of the paper

Explaining asset prices using SDF is a fundamental problem in finance

$$E_t(M_{t+1}R_{i,t+1}) = 0 \ \forall i, \text{ where } M_{t+1} \text{ is the SDF} \tag{1}$$

For e.g., in a **CAPM** world $M_{t+1} = a + bMkt_{t+1}$, for some a, $b \in \mathcal{R}$

Essence of the paper

Explaining asset prices using SDF is a fundamental problem in finance

$$E_t(M_{t+1}R_{i,t+1}) = 0 \ \forall i, \text{ where } M_{t+1} \text{ is the SDF} \tag{1}$$

For e.g., in a **CAPM** world $M_{t+1} = a + bMkt_{t+1}$, for some a, $b \in \mathcal{R}$

However, evidence shows that linear SDFs do not explain asset returns well

- Frazzini and Pedersen (2014), Ang et al (2006) document **pricing residuals** from "**linear asset pricing models**" explain asset returns

Essence of the paper

Explaining asset prices using SDF is a fundamental problem in finance

$$E_t(M_{t+1}R_{i,t+1}) = 0 \ \forall i, \text{ where } M_{t+1} \text{ is the SDF} \tag{1}$$

For e.g., in a **CAPM** world $M_{t+1} = a + bMkt_{t+1}$, for some a, $b \in \mathcal{R}$

However, evidence shows that linear SDFs do not explain asset returns well

- Frazzini and Pedersen (2014), Ang et al (2006) document **pricing residuals** from "**linear asset pricing models**" explain asset returns
- A limitation of these studies is that pricing residuals change with the benchmark linear model

Essence of the paper

Explaining asset prices using SDF is a fundamental problem in finance

$$E_t(M_{t+1}R_{i,t+1}) = 0 \;\forall i, \text{ where } M_{t+1} \text{ is the SDF} \tag{1}$$

For e.g., in a **CAPM** world $M_{t+1} = a + bMkt_{t+1}$, for some a, $b \in \mathcal{R}$

However, evidence shows that linear SDFs do not explain asset returns well

- Frazzini and Pedersen (2014), Ang et al (2006) document **pricing residuals** from "**linear asset pricing models**" explain asset returns
- A limitation of these studies is that pricing residuals change with the benchmark linear model

This paper: Generalized model for pricing residuals (w.r.t linear SDFs)

Essence of the paper

Explaining asset prices using SDF is a fundamental problem in finance

$$E_t(M_{t+1}R_{i,t+1}) = 0 \ \forall i, \text{ where } M_{t+1} \text{ is the SDF} \quad (1)$$

For e.g., in a **CAPM** world $M_{t+1} = a + bMkt_{t+1}$, for some a, $b \in \mathcal{R}$

However, evidence shows that linear SDFs do not explain asset returns well

- Frazzini and Pedersen (2014), Ang et al (2006) document **pricing residuals** from "**linear asset pricing models**" explain asset returns
- A limitation of these studies is that pricing residuals change with the benchmark linear model

This paper: Generalized model for pricing residuals (w.r.t linear SDFs)

- Builds on Hansen and Jagannathan framework
- Linear SDFs violate no-arbitrage restriction
- So, adds non-linear SDF to the linear SDF to yield no-arbitrage, and calls the non-linear SDF as the pricing residual

Contribution 1: Decomposing SDFs

The paper starts with incomplete markets assumption

- So, many candidate SDFs that price returns
- Choose the minimum variance SDF,

$$\min E_t(M_{t+1}^2) \text{ with } E_t(M_{t+1} R_{i,t+1}) = 0, \forall i, \text{ and } M_{t+1} > 0 \qquad (2)$$

Contribution 1: Decomposing SDFs

The paper starts with incomplete markets assumption

- So, many candidate SDFs that price returns
- Choose the minimum variance SDF,

$$\min E_t(M_{t+1}^2) \text{ with } E_t(M_{t+1}R_{i,t+1}) = 0, \forall i, \text{ and } M_{t+1} > 0 \quad (2)$$

The paper considers SDF candidates in a **polynomial space**

$$M_{t+1} = \underbrace{C_0 + \sum_i C_{it} R_{i,t+1}}_{Linear(M^*)} + \underbrace{\sum C_{\alpha t} R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \ldots R_{nt+1}^{\alpha_n}}_{Nonlinear(M^O)} \quad (3)$$

Contribution 1: Decomposing SDFs

The paper starts with incomplete markets assumption

- So, many candidate SDFs that price returns
- Choose the minimum variance SDF,

$$\min E_t(M_{t+1}^2) \text{ with } E_t(M_{t+1}R_{i,t+1}) = 0, \forall i, \text{ and } M_{t+1} > 0 \quad (2)$$

The paper considers SDF candidates in a **polynomial space**

$$M_{t+1} = \underbrace{C_0 + \sum_i C_{it} R_{i,t+1}}_{Linear(M^*)} + \underbrace{\sum C_{\alpha t} R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \dots R_{nt+1}^{\alpha_n}}_{Nonlinear(M^O)} \quad (3)$$

Thus, $M_{t+1} = M_{t+1}^* + M_{t+1}^O$, where $M_{t+1}^* \ngtr 0$, but $M_{t+1} > 0$

Contribution 1: Decomposing SDFs

The paper starts with incomplete markets assumption

- So, many candidate SDFs that price returns
- Choose the minimum variance SDF,

$$\min E_t(M_{t+1}^2) \text{ with } E_t(M_{t+1}R_{i,t+1}) = 0, \forall i, \text{ and } M_{t+1} > 0 \tag{2}$$

The paper considers SDF candidates in a **polynomial space**

$$M_{t+1} = \underbrace{C_0 + \sum_i C_{it} R_{i,t+1}}_{Linear(M^*)} + \underbrace{\sum C_{\alpha t} R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \dots R_{nt+1}^{\alpha_n}}_{Nonlinear(M^O)} \tag{3}$$

Thus, $M_{t+1} = M_{t+1}^* + M_{t+1}^O$, where $M_{t+1}^* \ngtr 0$, but $M_{t+1} > 0$

The paper shows $M^* \perp M^O$, and calls M^O mispricing SDF

Contribution 2: Estimating SDFs

Estimating the SDF involves computation of conditional return moments $\left(E\left[R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \ldots R_{nt+1}^{\alpha_n} | Z_t\right]\right)$

Contribution 2: Estimating SDFs

Estimating the SDF involves computation of conditional return moments $(E\left[R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \ldots R_{nt+1}^{\alpha_n} | Z_t\right])$

The paper uses the kernel-trick to estimate the conditional moments

Contribution 2: Estimating SDFs

Estimating the SDF involves computation of conditional return moments $\left(E\left[R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \dots R_{nt+1}^{\alpha_n} | Z_t\right]\right)$

The paper uses the kernel-trick to estimate the conditional moments

Intuition for kernel-trick: Suppose the goal is to estimate $E\left[R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \dots R_{nt+1}^{\alpha_n} | Z^*\right]$

Contribution 2: Estimating SDFs

Estimating the SDF involves computation of conditional return moments $\left(E\left[R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \ldots R_{nt+1}^{\alpha_n} | Z_t\right]\right)$

The paper uses the kernel-trick to estimate the conditional moments

Intuition for kernel-trick: Suppose the goal is to estimate $E\left[R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \ldots R_{nt+1}^{\alpha_n} | Z^*\right]$

- Go back to the past data and find periods "t" s.t $Z_t \approx Z^*$
- Take the sample average of $R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \ldots R_{nt+1}^{\alpha_n}$ over the similar periods t

Contribution 2: Estimating SDFs

Estimating the SDF involves computation of conditional return moments $\left(E\left[R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \dots R_{nt+1}^{\alpha_n} | Z_t\right]\right)$

The paper uses the kernel-trick to estimate the conditional moments

Intuition for kernel-trick: Suppose the goal is to estimate $E\left[R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \dots R_{nt+1}^{\alpha_n} | Z^*\right]$

- Go back to the past data and find periods "t" s.t $Z_t \approx Z^*$
- Take the sample average of $R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \dots R_{nt+1}^{\alpha_n}$ over the similar periods t

To be precise, take the weighted average of $R_{1t+1}^{\alpha_1} R_{2t+1}^{\alpha_2} \dots R_{nt+1}^{\alpha_n}$, where weights are proportional to $k(Z_t, Z^*)$

Empirical Contribution

The paper examines the cross-section of aggregate equity, short-term bonds, and exchange rates of US, UK, Canada, Switzerland, New Zealand, Japan, and Euro area

Empirical Contribution

The paper examines the cross-section of aggregate equity, short-term bonds, and exchange rates of US, UK, Canada, Switzerland, New Zealand, Japan, and Euro area

Key Findings

1. Residual mispricing (RMP) relates to financial uncertainty
2. RMP positively priced in the cross-section
3. RMP relates to financial distress (intermediary squared leverage)
4. RMP relates to market-wide liquidity shocks
5. RMP high during high periods of liquidity

Question 1:

To estimate conditional expected returns, the paper uses information only from two variables: $Z_t = \{\text{interest rate differentials, realized volatility}\}$

Question 1:

To estimate conditional expected returns, the paper uses information only from two variables: $Z_t = \{\text{interest rate differentials, realized volatility}\}$

Question: How robust is this specification?

Question 1:

To estimate conditional expected returns, the paper uses information only from two variables: $Z_t = \{\text{interest rate differentials, realized volatility}\}$

Question: How robust is this specification?

1. For e.g., Pelger,Chen, and Zhu (2020) consider linear SDFs with no-arbitrage
2. PCZ's SDF $= M_{t+1}^{PCZ} = 1 - \sum w_{it} R_{i,t+1}$, where w_{it} exploits "large information"
3. **In contrast to this paper**, pricing error of M_{t+1}^{PCZ} during crises is small
4. IVOL is negatively priced, whereas RMP is positively priced. Why?

Question 1:

To estimate conditional expected returns, the paper uses information only from two variables: $Z_t = \{\text{interest rate differentials, realized volatility}\}$

Question: How robust is this specification?

1. For e.g., Pelger,Chen, and Zhu (2020) consider linear SDFs with no-arbitrage
2. PCZ's SDF $= M_{t+1}^{PCZ} = 1 - \sum w_{it} R_{i,t+1}$, where w_{it} exploits "large information"
3. **In contrast to this paper**, pricing error of M_{t+1}^{PCZ} during crises is small
4. IVOL is negatively priced, whereas RMP is positively priced. Why?

So, if Z_t contains more information, would the results still hold?

Question 1:

To estimate conditional expected returns, the paper uses information only from two variables: $Z_t = \{$interest rate differentials, realized volatility$\}$

Question: How robust is this specification?

1. For e.g., Pelger,Chen, and Zhu (2020) consider linear SDFs with no-arbitrage
2. PCZ's SDF $= M_{t+1}^{PCZ} = 1 - \sum w_{it} R_{i,t+1}$, where w_{it} exploits "large information"
3. **In contrast to this paper**, pricing error of M_{t+1}^{PCZ} during crises is small
4. IVOL is negatively priced, whereas RMP is positively priced. Why?

So, if Z_t contains more information, would the results still hold?

Related question: How would you decide on what information set to use?

Question 2:

RMP is defined w.r.t $M_t^* = C_0 + \sum_i C_{it} R_{i,t+1}$, which is the non-positive linear SDF of Hansen and Jagannathan

Question 2:

RMP is defined w.r.t $M_t^* = C_0 + \sum_i C_{it} R_{i,t+1}$, which is the non-positive linear SDF of Hansen and Jagannathan

Question: How standard is this benchmark linear model?

Question 2:

RMP is defined w.r.t $M_t^* = C_0 + \sum_i C_{it} R_{i,t+1}$, which is the non-positive linear SDF of Hansen and Jagannathan

Question: How standard is this benchmark linear model?

1. For e.g., the paper calls this model "linear **market** model"
2. However, shouldn't the market SDF contain the market factor, i.e., $M_t^{mkt} = a + bMkt_t$?
3. Thus, M_t^{mkt} need not be equal to M_t^*?
4. Likewise, how close is M_t^* relative to the (SDF implied by) common linear risk factors documented in the international equity markets?

Question 3:

RMP uses current return information, $M^{O}_{t+1} = \sum C_{\alpha} R^{\alpha_1}_{1t+1} R^{\alpha_2}_{2t+1} \dots R^{\alpha_n}_{nt+1}$

Question 3:

RMP uses current return information, $M^{O}_{t+1} = \sum C_\alpha R^{\alpha_1}_{1t+1} R^{\alpha_2}_{2t+1} \ldots R^{\alpha_n}_{nt+1}$

Question: So, is RMP an **ex-post** measure?

Question 3:

RMP uses current return information, $M^{O}_{t+1} = \sum C_{\alpha} R^{\alpha_1}_{1t+1} R^{\alpha_2}_{2t+1} \dots R^{\alpha_n}_{nt+1}$

Question: So, is RMP an **ex-post** measure?

If yes, would it be possible to **ex-ante** identify when linear models have large pricing errors?

- For e.g., BAB, IVOL are ex-ante measures

Conclusion

1. Very interesting paper!
2. Personally, have learned a lot from the paper
3. Look forward to reading an updated version