Demand System Asset Pricing Research Questions

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Research questions

- Demand system asset pricing provides a new approach to asset pricing by studying the asset demand system using data on portfolio holdings.
- This is a new approach and this means that there are many open, unanswered questions.

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- This is a new approach and this means that there are many open, unanswered questions.
- In these final slides, we discuss a series of research questions that we find interesting and that (we think) are ripe for exploration.
- This list is by no means exhaustive, and make sure to reach out if we can be of help to provide feedback on a research idea that you are considering (myogo@princeton.edu and ralph.koijen@chicagobooth.edu)

- A large literature tries to understand the pricing of macroeconomic risks.
- Some interesting recent examples:

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- Inflation risk (Fang, Liu, and Roussanov, 2021).
- Political uncertainty (Kelly, Pastor, and Veronesi, 2016).
- Climate risk (Pastor, Stambaugh, and Taylor, 2022).
- Duration risk (Gormsen and Lazarus, 2022).

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- To understand whether macroeconomic risks are priced, it is common practice to implement the two-pass cross-sectional regression or Fama-MacBeth procedure.
- For instance, suppose we are interested in the price of a risk factor F_t in addition to the market risk factor, r^m_t:
 - 1. Estimate the factor betas using time-series regressions:

$$r_t(n) = a_n + \beta_n r_t^m + \gamma_n^F F_t + \epsilon_t(n).$$

2. Estimate the factor risk prices using cross-sectional regressions:

$$\overline{r}(n) = \alpha_n + \beta_n \lambda_m + \gamma_n^F \lambda^F,$$

where $\overline{r}(n)$ is the average return on stock *n*.

- We can use the demand system to provide a new perspective on each step.
- ▶ We start from the identity:

$$r_t(n) = \sum_{i=1}^l \Delta p_{i,t}(n) + v_t(n),$$

where $v_t(n)$ is the dividend yield.

As in Homework #3, $\Delta p_{i,t}(n)$ is the price movement for asset n due to institution i.

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- The return decomposition implies (assuming $F_t \perp r_t^m$):

$$\gamma_n^F = \sum_{i=1}^{I} \frac{Cov(\Delta p_{i,t}(n), F_t)}{V(F_t)} + \sum_{i=1}^{I} \frac{Cov(v_t(n), F_t)}{V(F_t)}$$

 We can therefore decompose the beta by investor or groups of investors.

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- We can therefore decompose the beta by investor or groups of investors.
 - Retail investors, hedge and mutual funds, pension funds, ...
 - Large and small investors, active and passive investors, ...
- This logic extends to the broader financial econometrics literature, including time-varying volatility, correlations, skewness, crash risk, ...

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- We can augment the demand equation:

$$\ln\left(\frac{w_i(n)}{w_i(0)}\right) = \beta_{0,i}me_t(n) + \beta'_{1i}x_t(n) + \beta_{2i}\gamma^F_n + \ln\left(\epsilon_{it}(n)\right).$$

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We can set β_{2i} to zero for different investor groups to see how the risk prices (and valuations) are affected. #3: Decomposing anomalies

► A large literature relates expected returns to characteristics:

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As before, we can use the return decomposition

$$\mathbb{E}\left[\sum_{i=1}^{l} \Delta p_{i,t+1}(n) + v_{t+1}(n) \mid \mathbf{x}_{t}(n)\right] = g(\mathbf{x}_{t}(n)).$$

- We can ask how a given characteristic predicts the return due to a group of investors.
- E.g., which investors drive momentum profits, the 5-factor Fama and French and the Q model, ...

#4: The factor zoo and the role of latent demand

- We have seen that latent demand is the key driver of cross-sectional stock returns.
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- We have seen that latent demand is the key driver of cross-sectional stock returns.
- In KY19, we use a fairly small number of characteristics, in particular in comparison to the recent literature on the "factor zoo."
- Can additional characteristics explain latent demand? How important are nonlinearities and interactions?
- Asset demand systems with many characteristics is a natural application for modern machine learning methods given the high dimensionality and abundance of data.
- Recent example: Zheng (2022).

#5: Models of beliefs and asset demand systems

- An exciting recent literature explores the role of beliefs and deviations from rational expectations from asset pricing.
 - E.g., Bordalo, Gennaioli, LaPorta, and Shleifer (2019) and Nagel and Xu (2022).

#5: Models of beliefs and asset demand systems

- An exciting recent literature explores the role of beliefs and deviations from rational expectations from asset pricing.
 - E.g., Bordalo, Gennaioli, LaPorta, and Shleifer (2019) and Nagel and Xu (2022).
- Suppose we allow for rational learning, diagnostic expectations, experience-based learning, what are the implied dynamics of holdings?
- If we estimate the structural parameters of the model (including the prior), allowing for heterogeneity across investors, how well do we fit holdings? Do the implied beliefs share the same dynamics as survey-based beliefs?
- Recent example: Chaudhry (2022).

#6: International finance

- In Koijen and Yogo (2021), we estimate an international asset demand system for short-term bonds, long-term bonds, and equities with implications for exchange rates.
- An international asset demand system can provide a new perspective on the central questions in international finance:
 - 1. Which countries drive the global financial cycle (Rey, 2013)?
 - 2. Which flows (equities, fixed income, FDI, ...) are most important in determining exchange rates?
 - 3. What drives the comovement of global yield curves and equity markets? What about convenience yields?
- Recent example: Jiang, Richmond, and Zheng (2022) use the international asset demand system to understand global imbalances.

#7: Modeling the household sector

Some early evidence based on DSAP are consistent with the household finance literature.

- ▶ However, we can only learn so much from aggregated data.
- More granular data from Sweden, Norway, or even incomplete U.S. data could help us unlock the household sector.
- A complete asset pricing model requires
 - Outer nest: Households allocate wealth to different institutions including 401(k) plans, mutual funds outside retirement accounts, insurance companies, direct holdings, etc.
 - 2. Inner nest: Each institution allocates AUM across securities.

#8: Substitution patterns

- The logit model implies fairly rigid substitution patterns at the investor level.
 - Once aggregated across investors, the substitution patterns are richer (see Berry, Levinsohn, and Pakes, 1995).
- How can we model richer substitution patterns? E.g. the demand for Apple depends on Google's characteristics or the demand for Italian bonds depends on the characteristics of Greece.

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- How can we model richer substitution patterns? E.g. the demand for Apple depends on Google's characteristics or the demand for Italian bonds depends on the characteristics of Greece.
- Potential approaches:
 - Random coefficients.
 - Nested logit.
 - Can we estimate the nesting and group structure? See, e.g., Almagro and Manresa (2019).

#9: Beyond equities

- We have focused largely on US equity markets.
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- However, rich holdings data are available across countries and asset classes (see also lecture 1).
- Of particular interest are:
 - Corporate bonds (Bretscher, Schmid, Sen, and Sharma, 2021).
 - Real and nominal bonds and thus break-even inflation.
 - Option markets (Who drives fluctuations in the VIX?).
 - Crypto currencies (Benetton and Compiani, 2021).

#10: Theory: Micro foundations of demand elasticities

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- A key new fact in asset pricing is that demand curves are surprisingly inelastic compared to theories.
- ▶ There is a dearth of theories that can explain this new fact.
- Potential explanations:

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- Uncertainty / ambiguity in estimating expected returns.
- Benchmarking and other institutional constraints.
- Risk parity, trend following, ...
- Overly strong belief in market efficiency.

#11: Theory: Micro foundations of demand curves

- Beyond the elasticity, how can we micro found the demand for characteristics and latent demand?
- There are many theories of institutional constraints, beliefs, ... that make predictions about the other coefficients.
- In addition to micro foundations of demand curves for the investors' holdings, another important direction for future research is to explain "the zeroes."

#12: High-frequency holdings/flows and event studies

- In some countries (e.g., Brazil, China, South Korea), detailed holdings data exist even at a daily frequency.
- This opens up an array of new questions:

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- Which investors trade around macroeconomic announcements (e.g., FOMC meetings)?
- Which investors price earnings news? ... and which investors are responsible for the post-earnings announcement drift?

Conclusion

- These are just initial suggestions and ideas.
- In case you are wondering whether a research idea is viable or how to best approach it, feel free to reach out.
- Keep in mind that this is a new area, so there are many (perhaps) seemingly obvious, and yet important, questions that are unexplored.
- Above all, we think that the asset demand system plays a central role in macro finance, and that improving our understanding of it is essential.