Section 5: A Demand System Approach to Asset Pricing

Ralph S.J. Koijen Stijn Van Nieuwerburgh* October 5, 2020

^{*}Koijen: University of Chicago, Booth School of Business, NBER, and CEPR. Van Nieuwerburgh: Columbia Business School, CEPR, and NBER. If you find typos, or have any comments or suggestions, then please let us know via ralph.koijen@chicagobooth.edu or svnieuwe@gsb.columbia.edu.

1. Basic structure of the notes

- High-level summary of theoretical frameworks to interpret empirical facts.
- Per asset class, we will discuss:
 - 1. Key empirical facts in terms of prices (unconditional and conditional risk premia) and asset ownership.
 - 2. Interpret the facts using the theoretical frameworks.
 - 3. Facts and theories linking financial markets and the real economy.
 - 4. Active areas of research and some potentially interesting directions for future research.
- The notes cover the following asset classes:
 - 1. Equities (weeks 1-5).
 - Predictability and the term structure of risk (week 1)
 - The Factor Zoo (week 2)
 - Intermediary-based Asset Pricing (week 3)
 - Production-based asset pricing (week 4)
 - Demand-based asset pricing (week 5)
 - 2. Mutual Funds and Hedge Funds (week 6).
 - 3. Options and volatility (week 7).
 - 4. Government bonds (week 8).
 - 5. Corporate bonds and CDS (week 9).
 - 6. Currencies and international finance (week 10).
 - 7. Commodities (week 11).
 - 8. Real estate (week 12).

2. Outline

- 1. Introduction to demand systems in asset pricing.
- 2. Connecting demand systems to traditional models in finance.
- 3. Estimating asset demand systems.
- 4. Demand systems and the cross-section of US stock returns: Measuring liquidity, decomposing returns, and predictability.
- 5. Decomposing equity valuations using demand systems.
- 6. A global demand system for FX, bond, and stock markets.

Note: These lecture notes are a summary of the notes developed for the 2020 summer school on Demand System Asset Pricing, organized jointly by Ralph Koijen, Robert Richmond, and Motohiro Yogo. Further details can be found at financialmarketinsights.com.

3. Modern approaches to asset pricing

- Much of asset pricing evolves around models of the stochastic discount factor (SDF, "*M*").
- Broadly speaking, there are four classes of models:
 - Empirical models with traded factors.
 E.g., Fama and French, Hou, Xue, and Zhang, Asness, Moskowitz, and Pedersen, as well as much of the recent machine-learning literature.
 - Empirical models with non-traded factors.
 E.g., Chen, Roll, and Ross and much of the work using macroeconomic series as pricing factors.
 - Euler equation models of a class of investors.
 E.g., Vissing-Jorgensen, as well as the recent literature on broker-dealers.
 - Macro-finance models.
 E.g., Campbell and Cochrane, Bansal and Yaron, Barro, Gabaix, and Wachter.
- How do we measure success? $\mathbb{E}[MR] = 1$.

- However, current models inadequate to answer some key questions.
 - Central questions surrounding financial markets are "quantity questions"
 - 1. How much do prices of Treasuries, MBS, credits, . . . move when the FED purchases \$100bn of corporate bonds?
 - 2. How does the growth of ESG, smart beta, and passive investing affect valuations and expected returns?
 - 3. How does the global savings glut (or, the savings glut of the rich) impact fixed income markets?
 - 4. How much do retail investors contribute to the recent rally in the stock market?
 - The modern asset pricing models are not set up to answer these questions.
 - * No market clearing (third class of models).
 - * Unrealistic demand elasticities.

- What is demand system asset pricing?
 - The goal of demand system asset pricing is to jointly explain asset prices, asset characteristics, macro fundamentals, and portfolio quantities.
 - Indeed, like anywhere else in economics, we are interested in understanding both prices and quantities, not just prices.
 - How does this differ from traditional asset pricing research?
 - 1. New data: Use portfolio holdings in equilibrium asset pricing.
 - 2. New methods: Estimating asset demand curves.
 - 3. New measures of success: Realistic empirical models and theoretical micro foundations of demand curves explaining how demand curves depend on beliefs, agency frictions, regulation, risk constraints,
 - A successful model of the asset demand system, combined with market clearing, *implies* a successful asset pricing model.

- Connecting the SDF and demand system approaches
 - Any asset pricing model that starts from preferences, beliefs, ..., implies
 - 1. An SDF that can be used to price assets using $\mathbb{E}[MR] = 1$.
 - 2. A demand system, $Q_i(P)$, that can be used to price assets by imposing market clearing, $\sum_i Q_i(P) = S$.
 - Additional reasons to study asset demand systems
 - 1. Testing theories Demand curves depend on ex-ante information and can provide more powerful tests of asset pricing models than Euler equation tests that average ex-post returns.
 - 2. New moments By testing the model's implications for demand curves (e.g., demand elasticities and crosselasticities), we expand the set of testable moments in a meaningful way.
 - As we will see, it makes asset pricing more "tangible" and removes some of the "dark matter."
 - Demand-based approach explored in the 60s and 70s by Brainard, Friedman, Tobin, and others.

4. Demand elasticities in standard asset pricing models

- In modeling investors' demand curves, elasticities and crosselasticities are key.
- Asset pricing theories generally imply downward-sloping demand.
 - Risk aversion, inter-temporal hedging demand (Merton, 1973), price impact (Wilson, 1979, and Kyle, 1989).
- It is a quantitative question: What is the slope of the demand curve?
- Let us consider a standard CAPM calibration following Petajisto (2009) to fix ideas.

CARA - normal model:

- N stocks with supply u_n each.
- Risk-free rate with infinitely-elastic supply, normalized to 0.
- Liquidating dividend for stock n

$$X_n = a_n + b_n F + e_n,$$

where F is the common factor and e_n the idiosyncratic risk.

• Distributional assumptions

$$F \sim N(0, \sigma_m^2), \qquad e_n \sim N(0, \sigma_e^2).$$

• There exists a continuum of investors that aggregate to a representative consumer with CARA preferences

$$\max_{\theta_i} E[-\exp(-\gamma W)], \quad W = W_0 + \sum_{n=1}^N \theta_n (X_n - P_n).$$

• Solving for equilibrium demand and set it equal to supply, u_n

$$P_n = a_n - \gamma \left[\sigma_m^2 \left(\sum_{m \neq n} u_m b_m \right) b_n + (\sigma_m^2 b_n^2 + \sigma_e^2) u_n \right].$$

The price discount will be dominated by the first term, not supply (the second term).

• Calibration

- N = 1000, $a_i = 105$, $b_i = 100$, $\sigma_e^2 = 900$, $\sigma_m^2 = 0.04$, $u_i = 1$, $\gamma = 1.25 \times 10^{-5}$.

 \Rightarrow Market risk premium equals 5%, all stocks have a price of 100, a market beta of 1, and a standard deviation idiosyncratic risk of 30%.

- A supply shock of -10% to a stock: $u_n = 0.9$ for one stock.
- The price of the stock increases by 0.16bp.
- Part of this increase is due to the reduction in the aggregate market risk premium as there is less aggregate risk
 ⇒ All stocks increase by 0.05bp.
- Hence, the differential impact is only 0.11bp. This is what we mean with virtually flat demand curves.
- Intuitively, stocks are just very close substitutes. What matters most is a stock's beta and its contribution to aggregate risk.
- Price elasticity of demand: $-\frac{\Delta Q/Q}{\Delta P/P} = \frac{0.10}{0.000016} \simeq 6,250.$
- Most of the literature focuses on the micro elasticity (substitute stock A for stock B), not the macro elasticity (move money from bonds to stocks).
- In the model, the market is more micro elastic than macro elastic.
 - Indeed, Apple and Google are closer substitutes than bonds and stocks.
- See Gabaix and Koijen (2020) for an analysis of the macro elasticity of the aggregate market, a comparison to traditional models, and estimates using the GIV methodology.

5. Empirical estimates of the micro elasticity

- Harris and Gurel (1986) and Shleifer (1986) look at the impact of stocks that are included in the S&P500 index.
- If (i) index inclusions are exogenous and (ii) a fraction of investors inelastically allocates capital to stocks included in the index, then we can measure the slope of demand curves.
- Importantly, in this literature, we can measure $\Delta \ln P$ quite well, but not $\Delta \ln Q$.
- Index providers run surveys to estimate the assets tracking their benchmarks.
- See for instance Chang, Hong, and Liskovich (2015):

Table 1

Assets benchmarked to indexes

Panel A: Passive assets									
	1996	1997	1998	1999	2000	2001	2002	2003	
Russell 2000	11.6	7.6	11.0	13.6	18.9	21.5	26.9	24.6	
Russell 1000	20.9	20.7	19.0	25.9	17.3	34.0	35.6	37.2	
	2004	2005	2006	2007	2008	2009	2010	2011	
Russell 2000	38.9	39.2	43.0	51.7	38.5	38.4	56.8	60.1	
Russell 1000	84.9	93.3	151.9	175.8	144.8	104.4	137.1	125.8	
Panel B: Assets	benchmarl	ked							
Number of produ	ucts	2002	2003	2004	2005	2006	2007	2008	
S&P 500	1	,009	924	919	901	888	824	685	
Russell 2000		289	255	264	275	273	511	449	
Russell 1000		29	43	43	48	52	52	60	
Dollar amount		2002	2003	2004	2005	2006	2007	2008	
S&P 500	1	,679.8	1,096.9	1,431.8	1,482.9	1,576.7	1,748.6	1,412.1	
Russell 2000		198.2	140.7	162.5	201.4	221.1	291.4	263.7	
Russell 1000		47.6	37.3	66.9	90.0	146.1	172.7	168.6	

Panel A reports the dollar amount of passive assets, in billions, benchmarked to the Russell 1000 and Russell 2000 by year. The data come from Russell's internal unaudited survey of its clients at the end of June. Panel B reports the number of products and dollar amount (in billions) of institutional assets benchmarked to the Russell 2000, Russell 1000, and S&P 500. These numbers are taken from Russell Investment's 2008 U.S. Equity Indexes: Institutional Benchmark Survey. The products surveyed are primarily institutional-oriented mutual funds, separate accounts, and commingled funds at the end of May.

- Evidence from Russell additions and deletions
 - Based on Chang, Hong, and Liskovich (2015), the returns due to addition/deletions from Russell indices:

Returns	s fuzzy RD				
Addition	n effect				
	May	Jun	Jul	Aug	Sep
D	-0.003 (-0.14)	0.050** (2.65)	-0.003 (-0.11)	0.035 (1.59)	-0.021 (-0.89)
N	1055	1057	1053	1052	1047
Deletion	effect				
	May	Jun	Jul	Aug	Sep
D	0.005 (0.32)	0.054** (3.00)	-0.019 (-0.96)	-0.002 (-0.09)	0.011 (0.53)
N	1546	1545	1533	1526	1519

Table 4 Returns fuzzy RI

- Implied price elasticity of demand:

- * 1.5 if all assets benchmarked are used.
- * 0.4 if only passive assets are assumed to respond.

 \Rightarrow Demand is more inelastic in the second case as the price change is caused by a smaller demand shock (only passive assets).

- Barbon and Gianinazzi (2019) estimate a short- and longrun demand elasticity of one using Japan's equity QE program.
- Hence, demand is much less elastic than what is implied by the CAPM (recall: the demand elasticity is 6,250 in traditional models).

6. Towards an empirically-tractable model of demand

- Wish list for our model:
 - 1. Nests modern portfolio theory as a special case.
 - 2. Empirically tractable.
 - 3. Sufficiently flexible to allow for inelastic demand curves.
- Standard mean-variance portfolio choice implies

$$w = \frac{1}{\gamma} \Sigma^{-1} \mu.$$

- If we model $\mu(n)$ as a function of characteristics of stock n, x(n), as in modern empirical asset pricing, it seems intractable as characteristics of all stocks matter (via Σ^{-1}).
- Key insight: Solution simplifies under realistic assumptions to

$$w(n) = \frac{b'x(n)}{c},$$

where c encodes the information of all other stocks.

Investor types, preferences, and technology

- We consider two broad classes of investors: Quants and Fundamental investors.
- We have $i = 1, ..., I_x, x = Q, F$, investors of each type.
- Investors have CARA preferences

$$\max_{\mathbf{q}_{i}} \mathbb{E}\left[-\exp\left(-\gamma_{i} A_{1i}\right)\right],$$

with risk aversion coefficients $\gamma_i = \frac{1}{\tau_i A_{i0}}$ and initial assets A_{i0} .

- Investors allocate capital to $n = 1, \ldots, N$ assets.
- Intra-period budget constraint:

$$A_{0i} = \boldsymbol{q}_i' \boldsymbol{P}_0 + Q_i^0,$$

• Dividends are given by D_1 , which equal P_1 in a static model.

Quant investors (Koijen and Yogo, 2019)

- Let $\boldsymbol{R}_1 = \boldsymbol{P}_1 \boldsymbol{P}_0$ be the (dollar) return.
- Quants reason in terms of factor models and try to discover alpha as a function of asset characteristics

$$R_1 = a_i + \beta_i R_1^m + \eta_1,$$

$$\mu_i = \alpha_i + \beta_i \Lambda,$$

where $\boldsymbol{\mu}_i = \mathbb{E}_i \left[\boldsymbol{R}_1 \right]$ and $\operatorname{Var} \left(\boldsymbol{\eta}_1 \right) = \sigma^2 \boldsymbol{I}$.

• Hence, the covariance matrix of returns is

$$\boldsymbol{\Sigma}_i = \boldsymbol{\beta}_i \boldsymbol{\beta}_i' + \sigma^2 \boldsymbol{I}.$$

• Key: Alphas and betas are affine in characteristics,

$$\beta_i(n) = \boldsymbol{\lambda}_i^{\beta'} \boldsymbol{x}(n) + \nu_i^{\beta}(n),$$

$$\alpha_i(n) = \boldsymbol{\lambda}_i^{\alpha'} \boldsymbol{x}(n) + \nu_i^{\alpha}(n).$$

Fundamental investors (Koijen, Richmond, and Yogo, 2020)

- Let $\mathbf{R}_1^F = \mathbf{D}_1 \mathbf{P}_0$ the long-run fundamental return.
- Fundamental investors think about the long-run expected growth rate of fundamentals and their riskiness

$$\boldsymbol{D}_1 = \boldsymbol{g}_i + \boldsymbol{\rho}_i F_1 + \boldsymbol{\epsilon}_1,$$

where $\operatorname{Var}(\boldsymbol{\epsilon}_1) = \sigma^2 \boldsymbol{I}$.

• Hence, the covariance matrix of long-horizon returns is

$$\boldsymbol{\Sigma}_i^F = \boldsymbol{\rho}_i \boldsymbol{\rho}_i' + \sigma^2 \boldsymbol{I}.$$

• Key: Factor loadings and expected growth are affine in characteristics,

$$\rho_i(n) = \boldsymbol{\lambda}_i^{\rho'} \boldsymbol{x}(n) + \nu_i^{\rho}(n),$$

$$g_i(n) = \boldsymbol{\lambda}_i^{g'} \boldsymbol{x}(n) + \nu_i^{g}(n).$$

Demand curves

• The quant's optimal portfolio is

$$oldsymbol{q}_i^Q = rac{1}{\gamma_i} oldsymbol{\Sigma}_i^{-1} oldsymbol{\mu}_i.$$

• The optimal portfolio of the fundamental investor is

$$\boldsymbol{q}_{i}^{F}=rac{1}{\gamma_{i}}\left(\boldsymbol{\Sigma}_{i}^{F}
ight)^{-1}(\boldsymbol{g}_{i}-\boldsymbol{P}_{0}).$$

Key insight

• In both cases, the demand curve takes the form

$$oldsymbol{q}_i = rac{1}{\gamma} \left(oldsymbol{v}_i oldsymbol{v}_i' + \sigma^2 I
ight)^{-1} oldsymbol{m}_i.$$

• Using the Woodburry matrix identity, we have

$$egin{array}{rcl} q_i &=& rac{1}{\gamma\sigma^2}\left(I-rac{oldsymbol{v}_ioldsymbol{v}_i}{oldsymbol{v}_ioldsymbol{v}_i+\sigma^2}
ight)oldsymbol{m}_i \ &=& rac{1}{\gamma\sigma^2}\left(oldsymbol{m}_i-c_ioldsymbol{v}_i
ight), \end{array}$$

where $c_i = \frac{v'_i m_i}{v'_i v_i + \sigma^2}$ is a scalar that encodes the information of all other stocks.

- The demand for stock *n* only depends on the characteristics of stock *n* and a common scalar, *c_i*.
- **Intuition:** The factor exposure is a sufficient statistic for the riskiness of stock *n*.

Solve for asset prices by imposing market clearing

• Market clearing

$$ME(n) = \sum_{i=1}^{I} A_i w_i(n).$$

• KY19 show that a unique equilibrium exists if demand is downward sloping for all investors.

7. Estimating an asset demand system for US equities

Challenges in estimating asset demand systems

- Latent demand is jointly endogenous with asset prices.
 - If investors are large, or latent demand is correlated across investors.
- Implementation choices.
 - Estimate with/without zero portfolio weights.
 - Investors with small number of assets in the portfolio.

Data source: 13F

- SEC Form 13F: Quarterly stock holdings of institutions managing over \$100m.
 - Types: Banks, insurance companies, investment advisors, mutual funds, pension funds, other.
 - Household sector.
- Merged with stock prices and characteristics in CRSP-Compustat.
- Big data: 44 million observations.

Summary of 13F institutions

		% of	Asset mana (\$ n	ts under agement nillion)	Nun stoc	nber of ks held	Numbe in inv un	r of stocks restment iverse
	Number of	market	90th			90th		90th
Period	institutions	held	Median	percentile	Median	percentile	Median	percentile
1980–1984	544	35	337	2,666	118	386	183	523
1985–1989	780	41	400	3,604	116	451	208	692
1990–1994	979	46	405	4,566	106	512	192	811
1995–1999	1,319	51	465	6,579	102	556	176	943
2000-2004	1,800	57	371	6,095	88	521	165	983
2005-2009	2,442	65	333	5,427	73	460	145	923
2010-2014	2,879	65	315	5,441	68	447	122	800
2015–2017	3,655	68	302	5,204	67	454	112	748

- Investment universe: Set of stocks that an institution is allowed to hold, determined by a mandate.
- Observed for some mutual funds (e.g., S&P 500 index fund).
- In practice, measured as stocks held currently or in past 11 quarters.

Persistence of the set of stocks held

AUM		Previous quarters									
percentile	1	2	3	4	5	6	7	8	9	10	11
1	82	85	86	88	89	90	91	92	93	93	94
2	85	87	89	91	92	92	93	94	94	95	95
3	85	88	89	90	91	92	93	93	94	94	95
4	85	87	89	90	91	92	92	93	93	94	94
5	85	87	89	90	90	91	92	92	93	93	94
6	85	87	88	89	90	91	92	92	93	93	94
7	84	86	88	89	90	91	91	92	92	93	93
8	84	87	88	90	90	91	92	92	93	93	94
9	87	89	90	91	92	93	93	94	94	94	95
10	92	93	94	95	95	96	96	96	97	97	97

Empirical specification

• Nonlinear GMM (with zero weights).

$$\frac{w_i(n)}{w_i(0)} = \exp\left\{\beta_{0,i} \operatorname{me}(n) + \sum_{k=1}^K \beta_{k,i} x_k(n)\right\} \epsilon_i(n)$$

- Moment condition: $\mathbb{E}[\epsilon_i(n)|\widehat{\mathrm{me}}_i(n),\mathbf{x}(n)] = 1.$

• Linear IV (without zero weights).

$$\log\left(\frac{w_i(n)}{w_i(0)}\right) = \beta_{0,i} \operatorname{me}(n) + \sum_{k=1}^K \beta_{k,i} x_k(n) + \log(\epsilon_i(n))$$

- Moment condition: $\mathbb{E}[\log(\epsilon_i(n))|\widehat{\mathrm{me}}_i(n), \mathbf{x}(n)] = 0.$

- Characteristics.
 - 1. Log book equity.
 - 2. Profitability.
 - 3. Investment.
 - 4. Dividends to book equity.
 - 5. Market beta.
- For each 13F institution and the household sector, use the cross-section of holdings to estimate coefficients at each point in time.
- Traditional assumption in endowment economies:

$$\mathbb{E}[\epsilon_i(n)|\mathrm{me}(n), \mathbf{x}(n)] = 1$$

Instrument: Version 1

- Factor structure implies that portfolio weight for Apple depends
 - Directly on Apple's price and characteristics.
 - Indirectly on the characteristics of other stocks (e.g., Amazon) through market clearing.
- Instrument:

$$\widehat{\mathrm{me}}_i(n) = \log\left(\sum_{j \neq i} A_j \widehat{w}_j(n)\right)$$

- $\hat{w}_j(n)$ are predicted weights from a regression of portfolio weights onto characteristics only.

Instrument: Version 2

$$\frac{w_i(n)}{w_i(0)} = \begin{cases} \exp\left\{\beta_{0,i} \operatorname{me}(n) + \sum_{k=1}^K \beta_{k,i} x_k(n)\right\} \epsilon_i(n) & \text{if } n \in \mathcal{N}_i \\ I_i(n) = 0 & \text{if } n \notin \mathcal{N}_i \end{cases}$$

- Investors may not hold an asset for two reasons.
 - 1. $\epsilon_i(n) = 0$: Chooses not to hold an asset.
 - 2. $I_i(n) = 0$: Cannot hold an asset outside the investment universe.
- Assumption: Investment universe is exogenous.
- Instrument:

$$\widehat{\mathrm{me}}_{i}(n) = \log\left(\sum_{j \neq i} A_{j} \frac{I_{j}(n)}{1 + \sum_{m=1}^{N} I_{j}(m)}\right)$$

Intuition

- Index addition/deletion (e.g., Shleifer 1986) relates exogenous changes in demand to returns.
- Apply the same logic to the level of prices. Heterogeneous investment universe creates exogenous variation in demand that relates to price.
- Stocks that appear in the investment universe of more investors (weighted by AUM) has higher price.
- Changes to the exogenous, residual demand curve (= net supply) help trace out the slope of the demand curve

Small number of assets in the portfolio

- For investors with at least 1,000 stocks in the portfolio, estimate coefficients individually.
- For investors with fewer stocks
 - Pooled estimation among investors of the same type and similar AUM (Koijen and Yogo 2019).
 - Ridge estimation by institution, shrinking toward the average coefficient for investors with at least 1,000 stocks (Koijen, Richmond, and Yogo 2020).
- Koijen and Yogo (2019) show that
 - 1. The instrument is not weak.
 - 2. OLS is upwardly biased (latent demand and asset prices are positively correlated).

- 3. The estimator correctly identifies the preferences of an index fund: coefficient of 1 on price (ME/BE and BE) and zero on all other characteristics.
- Coefficients on characteristics:



• Standard deviation of latent demand (across stocks for each investor, then asset weighted average among investors in each category):



• Households have less extreme positions, except in financial crisis.

8. Applications

Questions

- 1. Have financial markets become more liquid over the last 30 years with the growing importance of institutional investors?
- 2. How much of the volatility and predictability of asset prices is explained by institutional demand?
- 3. Do large investment managers amplify volatility? Should they be regulated as SIFIs (OFR 2013)?
- 4. How do large-scale asset purchases affect asset prices through institutional holdings?

• Application 1: Price impact across stocks and institutions.



- Price impact for each investor *i*: $\partial p(n) / \partial \log(\epsilon_i(n))$.

 Price impact has decreased over time, esp. for the smallest stocks at 90th percentile: compression in liquidity distribution.

- Aggregate price impact: $\sum_{i=1}^{I} \partial p(n) / \partial \log(\epsilon_i(n))$.



- Aggregate price impact for median stock has decreased.
 Effect of 10% aggregate demand shock was 26% in 2017.
- Price impact higher in recessions.

- Application 2: Variance decomposition of stock returns.
 - Start with definition of log return:

$$r_{t+1}(n) = p_{t+1}(n) - p_t(n) + \log\left(1 + \frac{D_{t+1}(n)}{P_{t+1}(n)}\right)$$

- Model implies that

$$\mathbf{p}_t = \mathbf{g}(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t)$$

- 1. s_t : Shares outstanding.
- 2. \mathbf{x}_t : Asset characteristics.
- 3. A_t : Assets under management.
- 4. β_t : Coefficients on characteristics.

5. ϵ_t : Latent demand.

- Variance decomposition of stock returns

	% of
	variance
Supply:	
Shares outstanding	2.1
	(0.2)
Stock characteristics	9.7
	(0.3)
Dividend yield	0.4
	(0.0)
Demand:	
Assets under management	2.3
	(0.1)
Coefficients on characteristics	4.7
	(0.2)
Latent demand: Extensive margin	23.3
	(0.3)
Latent demand: Intensive margin	57.5
	(0.4)
Observations	134,328

- Characteristics only explain 10% of the cross-sectional variation in returns (recall week 2 on the factor zoo).
- Investor characteristics matter: variation in the AUM distribution and in loadings on the characteristics explain 7%.
- Latent demand most important (80%)!
 - * Extensive: set of stocks,
 - * Intensive: within set of stocks held.
 - * Stock returns depend crucially on change in the mean of latent demand ("sentiment")
 - * and the dispersion of latent demand ("disagreement").

- Are large investment managers systemic (OFR 2013)? Variance decomposition of stock returns in 2008
 - Even small shocks to Blackrock could amplify price movements because of their sheer size. But, they are well diversified and hold more liquid stocks (less price impact). Empirical question.

AUM		AUM	Change in	%	of
ranking	Institution	(\$ billion)	AUM (%)	varia	nce
	Supply: Shares outstanding, stock				
	characteristics & dividend yield			8.1	(1.0)
1	Barclays Bank	699	-41	0.3	(0.1)
2	Fidelity Management & Research	577	-63	0.9	(0.2)
3	State Street Corporation	547	-37	0.3	(0.0)
4	Vanguard Group	486	-41	0.4	(0.0)
5	AXA Financial	309	-70	0.3	(0.1)
6	Capital World Investors	309	-44	0.1	(0.1)
7	Wellington Management Company	272	-51	0.4	(0.1)
8	Capital Research Global Investors	270	-53	0.1	(0.1)
9	T. Rowe Price Associates	233	-44	-0.2	(0.1)
10	Goldman Sachs & Company	182	-59	0.1	(0.1)
	Subtotal: 30 largest institutions	6,050	-48	4.4	
	Smaller institutions	6,127	-53	40.7	(2.3)
	Households	6,322	-47	46.9	(2.6)
	Total	18,499	-49	100.0	

- Application 3: Predictability of stock returns.
 - Recall that

$$\mathbf{p}_T = \mathbf{g}(\mathbf{s}_T, \mathbf{x}_T, \mathbf{A}_T, eta_T, \epsilon_T)$$

- Model ϵ_T as mean reverting and everything else as random walk.
- First-order approximation of expected long-run capital gain:

$$\mathbb{E}_t[\mathbf{p}_T - \mathbf{p}_t] \approx \mathbf{g}(\mathbb{E}_t[\mathbf{s}_T], \mathbb{E}_t[\mathbf{x}_T], \mathbb{E}_t[\mathbf{A}_T], \mathbb{E}_t[\beta_T], \mathbb{E}_t[\epsilon_T]) - \mathbf{p}_t$$
$$= \mathbf{g}(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \mathbf{1}) - \mathbf{p}_t$$

- Intuition: Assets with high latent demand are expensive and have low expected returns.

	All	Excluding
Characteristic	stocks	microcaps
Expected return	0.18	0.11
	(0.04)	(0.04)
Log market equity	-0.25	-0.15
	(0.08)	(0.08)
Book-to-market equity	0.04	0.06
	(0.04)	(0.05)
Profitability	0.30	0.29
	(0.06)	(0.06)
Investment	-0.38	-0.21
	(0.03)	(0.03)
Market beta	0.08	0.01
	(0.08)	(0.10)
Momentum	0.24	0.37
	(0.08)	(0.10)

- Relation between stock returns and characteristics.

- The measure of expected returns implied by the demand system predicts returns, beyond the characteristics of the Fama-French 5-factor model.
- An advantage of the demand system is that it uses only cross-sectional information and adjusts quickly to new themes in the market (e.g., COVID-19).

9. Valuation and long-horizon expected returns

- Large literature devoted to identifying firm characteristics that explain differences in asset prices.
 - * Firm fundamentals, measures of beliefs about returns or cash flows, and environmental, social, and governance (ESG) measures.
- Literature often provides narratives related to different types of investors whose asset demands reflect these characteristics.
 - * Arbitrageurs or hedge funds in search of mispricings, sentiment-driven retail investors, or pension funds and sovereign wealth funds with ESG mandates.
- In inelastic asset markets, differences in demand of individual investors is reflected in prices.
- We can use a demand system approach to *quantitatively* trace the connection between valuations, expected returns, and characteristics back to specific investors or groups of investors.

- A simple benchmark
 - Question: How much do valuations change if all institutions of a particular type switched to holding a marketweighted portfolio?
 - Assume that the demand elasticity equals one.
 - Given an investor's current holdings, compute the shift in demand required for a group of investors to switch to a market portfolio and multiply it by minus one, the approximate demand elasticity.
- Limitations of the simple benchmark
 - While intuitive, this simple calculation has three shortcomings
 - 1. It assumes the same unit elasticity for each stock.
 - * Stocks are held by different investors with heterogeneous demand elasticities.
 - 2. It ignores cross-elasticities.
 - * For example, we do not know how the price of Apple changes in response to a demand shock for Google.
 - 3. It cannot assess how much an investor contributes to incorporating information about specific characteristics into prices.
 - The demand system approach to asset pricing resolves all three problems.

- Data:
 - * Prices, fundamentals, and holdings from FactSet from 2006 to 2016.
 - * Prices and fundamentals for the EU, GB, JP, and US.
 - * Holdings for GB and US.
 - $\ast\,$ Focus on the top 90% of firms by market cap.
- We form the following investor groups

Туре	Investor	AUM
Households		6588
Inv. Large Passive	The Vanguard Group, Inc.	1598
Inv. Large Active	T. Rowe Price Associates, Inc.	423
Long-Term	Norges Bank Investment Management	199
Private Banking	Goldman Sachs & Co. LLC (Private Banking)	99
Inv. Small Passive	Managed Account Advisors LLC	94
Inv. Small Active	PRIMECAP Management Co.	84
Hedge Funds	AQR Capital Management LLC	62
Brokers	Credit Suisse Securities (USA) LLC (Broker)	60



- Institutional types have been stable over sample

- Valuation ratios and characteristics

- * Log book equity to capture size.
- * Measures of productivity and markups:
 - · Sales-to-book equity.
 - \cdot Lerner index.
 - · Foreign sales share.
 - · Dividend-to-book equity.
- * Market beta as a measure of equity market risk.
- Valuation ratios, profitability, and characteristics.

$$mb_t(n) = a_t + \lambda'_{mb}x_t(n) + \epsilon_t(n)$$

$$e_{t+5}^{(5)}(n) = a_t^e + \lambda'_e x_t(n) + \epsilon_t(n)$$

	United	States	Great H	Britain	Euro	Area	Jap	an
	mb	e^5	mb	e^5	mb	e^5	mb	e^5
Foreign Sales	0.16	0.07	0.12	0.08	0.12	0.02	0.10	0.00
	(21.61)	(5.52)	(5.85)	(1.83)	(7.75)	(2.69)	(7.73)	(0.34)
Lerner	0.06	0.13	0.06	0.15	0.11	0.08	0.13	0.10
	(5.27)	(9.74)	(2.75)	(3.43)	(6.22)	(8.57)	(11.92)	(6.81)
Sales to Book	0.19	0.19	0.21	0.16	0.14	0.06	0.15	0.09
	(30.52)	(18.48)	(5.82)	(2.02)	(16.67)	(4.29)	(17.54)	(20.20)
Dividend to Book	0.16	0.10	0.32	0.19	0.20	0.17	0.19	0.03
	(16.28)	(7.10)	(11.62)	(3.82)	(14.38)	(6.52)	(17.08)	(1.88)
Market Beta	-0.06	-0.02	-0.04	0.04	-0.04	-0.02	-0.01	0.03
	(-3.19)	(-1.03)	(-1.73)	(1.58)	(-2.63)	(-1.13)	(-0.31)	(2.08)
Log Book Equity	-0.46	-0.18	-0.45	-0.23	-0.43	-0.20	-0.23	-0.09
	(-36.12)	(-8.39)	(-12.82)	(-6.54)	(-47.96)	(-16.28)	(-12.25)	(-9.52)
Adj. R ²	0.54	0.33	0.70	0.52	0.61	0.38	0.42	0.28
Within Adj. \mathbb{R}^2	0.52	0.32	0.68	0.50	0.56	0.32	0.37	0.21
Observations	8537	3090	1638	539	3027	1124	7100	2800

- * $\lambda_{mb} \lambda_e$ relates long-term expected returns to characteristics.
- \ast Strong connection between ln(be) and expected returns.
- Use characteristics, x_t , to explain valuations and future profits:





- Estimates of demand curves across investor types

- Which investors matter for valuations and expected returns?
 - * Quantitative impact of investors varies due to differences in
 - · Assets under management.
 - Demand: Elasticities with respect to price and characteristics.
 - * The portfolio weight on stock n is

$$w_i(n) = \frac{\delta_i(n)}{1 + \sum_{m \in \mathcal{N}_i} \delta_i(m)},$$

where

$$\ln \delta_i(n) = b_{0,i} + \beta_{0,i} m b(n) + \beta'_{1,i} x(n) + \epsilon_i(n).$$

* We compute asset prices if a particular institutional type would hold the market portfolio

• $\beta_{0i} = 1$, $\beta_{1i} = e_1$, and $\epsilon_i(n) = 0$.

- Importance of investor types in the price formation process.



- Repricing = change in market cap (relative to total market cap) if a particular group of investors switch to holding the market portfolio.
- * Repricing is correlated with an institutional sector's size.
- * Bottom panel: ratio of repricing to ownership share
- * Per dollar of AUM (bottom panel), hedge funds are most influential.

- Importance by investor size quintile.



- Decomposing the link between prices and characteristics

	IA Large Pass.	IA Small Pass.	IA Small Act	IA Large Act	Hedge Funds	Long-Term	Priv. Banking	Brokers
Foreign Sales	-0.20	0.17	-1.73	-0.42	1.33	0.35	-0.24	0.09
Lerner	1.37	0.32	-1.19	0.72	1.20	-0.21	-0.42	0.09
Sales/Book	0.51	0.93	3.68	0.45	-0.98	0.37	-0.26	-0.02
Div./Book	-0.12	0.22	10.47	2.51	3.75	-0.30	0.30	-0.10
Market Beta	-0.37	-0.55	-0.22	-0.60	-2.13	-0.48	0.07	-0.23
Log BE	0.99	3.64	21.92	1.91	4.99	0.09	1.20	-0.05
R-squared	-1.88	-4.96	-16.26	-1.79	-4.92	-1.83	-1.23	-0.19

- Interpretation: The valuation difference of firms with a one standard deviation difference in dividend-to-book equity would increase by 10.47% if small, active investment advisors switch to strict market weights.
- Lower R^2 of small IA means that they are very important for impounding fundamental information into asset prices. This is largely due to their large total size. HF also very important, despite their smaller size.

 Map prices to expected returns using the present-value identity of Cohen, Polk, and Vuolteenaho (2003) and Campbell, Polk, and Vuolteenaho (2010):

$$mb_t(n) = \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t \left[e_{t+s}(n) \right] - \sum_{s=1}^{\infty} \rho^{s-1} \mathbb{E}_t \left[r_{t+s}(n) \right].$$

- Assuming random walks for expected returns and expected growth in cash flows (recall class 1), we get:

$$mb_t(n) = C + \frac{g_t}{1-\rho} - \frac{\mu_t}{1-\rho}$$

- Relation between dividend-to-book equity and expected returns would change by 52bp per year for 1 sd change.
- Note that small but highly persistent changes in per-period expected returns have large implications for valuations.
- Most of the literature focuses on short-horizon (monthly or quarterly) alphas.

10. A demand system for global financial markets

- Koijen and Yogo (2020) develop a global asset demand system to understand the determinants of exchange rates and asset prices.
- Global asset prices reflect:
 - * Global investors.
 - Hold financial assets (short-term debt, long-term debt, and equity) across many countries.
 - $\cdot\,$ Substitute within and across asset classes.
 - Demand depends on exchange rates and macro shocks.
 - * Policy.
 - · Short-term rates.
 - Debt quantities through fiscal and monetary policy.
 - Foreign exchange reserves: Central banks hold foreign assets.

- Data structure:
 - Annual data for 2002–2017 from the IMF's Coordinated Portfolio Investment Survey across 3 asset classes.
 - 1. Short-term debt.
 - 2. Long-term debt
 - 3. Equity.
 - Investors: 88 countries and foreign exchange reserves.
 - * Reserves: Central bank holdings of foreign assets.
 - 36 issuer countries with complete data on asset prices and characteristics.
 - * All 22 countries in the MSCI World Index.
 - * 14 of 21 countries in the MSCI Emerging Markets Index.
 - * Other countries aggregated as "outside asset" for each asset class.
 - Define supply as
 - * Debt: Total amount held by foreigners.
 - * Equity: Total stock market capitalization.

Top ten investors by asset class

Short-term of	lebt	Long-term de	ebt	Equity	Equity		
	Billion	_	Billion		Billion		
Investor	US\$	Investor	US\$	Investor	US\$		
Reserves	912	Reserves	4,381	United States	32,799		
Ireland	527	Japan	2,176	China	8,194		
United States	488	United States	2,165	Japan	5,343		
Luxembourg	361	Germany	2,002	Hong Kong	4,198		
France	215	Luxembourg	1,995	United Kingdom	2,867		
Cayman Islands	188	France	1,489	Canada	2,846		
United Kingdom	126	Ireland	1,317	France	1,971		
Hong Kong	111	United Kingdom	1,038	Luxembourg	1,952		
Singapore	84	Netherlands	909	India	1,828		
Switzerland	55	Cayman Islands	834	Australia	1,629		

- Offshore financial centers: Ireland, Luxembourg, and Cayman Islands. Suggestive evidence of downward-sloping demand across markets:

- Relative log quantity: $q_t(n) q_t(US)$.
- Relative log price: $p_t(n) + e_t(n) p_t(US)$.
- Scatter plots suggest inelastic demand for long-term debt and equity.

Relative long-term debt quantity and price



Relative equity quantity and price



Market clearing

• Market clearing for each country *n* and asset class *l*:

$$P_t(n,l)E_t(n)Q_t(n,l) = \sum_{i=1}^{I} A_{i,t}w_{i,t}(n,l;\mathbf{P}_t,\mathbf{E}_t)$$

- Supply:
 - $P_t(n, l)$: Market-to-book ratio (or price per unit of face value).
 - $E_t(n)$: Exchange rate in US\$ per country *n*'s currency unit.
 - $Q_t(n, l)$: Book (or face) value in country *n*'s currency unit.
- Demand:
 - $A_{i,t}$: Investor *i*'s wealth.
 - $w_{i,t}(n,l)$: Portfolio weight in country n and asset class l.

- Market clearing is a system of equations.
 - 1. Short-term debt: 26 countries plus euro area.
 - 2. Long-term debt: 36 countries.
 - 3. Equity: 36 countries.
- Conditional on short-term rate (central bank policy), the system determines:
 - 1. 26 exchange rates (relative to US\$).
 - 2. 36 long-term yields.
 - 3. 36 stock prices.
- A model of portfolio weights that
 - Matches cross-country holdings.
 - Easy to estimate demand elasticities.
 - Flexible substitution within and across asset classes.

Two extensions compared to the earlier model:

1. Nested logit to allow for imperfect substitution across asset classes.

$$w_{i,t}(n,l) = \underbrace{w_{i,t}(n|l)}_{\text{within}} \underbrace{w_{i,t}(l)}_{\text{across}}$$

- 2. Portfolio weights depend on expected returns in own currency unit.
 - Estimate a predictive regression for each asset class:

$$r_{t+1}(n,l) - y_t(\mathbf{US}) = \theta_l p_t(n,l) + \Theta_l(e_t(n) - z_t(n)) + \nu_{t+1}(n,l)$$

• Expected returns in investor *i*'s currency unit:

$$\mathbb{E}_{t}[r_{t+1}(n,l) - \Delta e_{t+1}(i) - y_{t}(i)] = \mu_{i,t}(n,l)$$

Allocation within asset class

• Portfolio weight in country n within asset class l.

$$w_{i,t}(n|l) = \frac{\delta_{i,t}(n,l)}{1 + \sum_{m=0}^{N} \delta_{i,t}(m,l)}$$

where

$$\log(\delta_{i,t}(n,l)) = \beta_l \mu_{i,t}(n,l) + \gamma'_l \mathbf{x}_{i,t}(n,l) + \epsilon_{i,t}(n,l)$$

- $\mathbf{x}_{i,t}(n,l)$: Observed characteristics.
- $\epsilon_{i,t}(n,l)$: Latent demand.

Allocation across asset classes

• Portfolio weight in asset class *l*.

$$w_{i,t}(l) = \frac{\left(1 + \sum_{m=0}^{N} \delta_{i,t}(m,l)\right)^{\lambda_l} \exp\{\alpha_l + \xi_{i,t}(l)\}}{\sum_{k=1}^{3} \left(1 + \sum_{m=0}^{N} \delta_{i,t}(m,k)\right)^{\lambda_k} \exp\{\alpha_k + \xi_{i,t}(k)\}}$$

- $\xi_{i,t}(l)$: Asset-class latent demand.
- Special cases:
 - $\lambda = 1$: Logit (Koijen and Yogo 2019).
 - $\lambda = 0$: No substitution across asset classes.

Estimation methodology:

- Observed characteristics.
 - Macro: Log GDP, log GDP per capita, inflation, equity volatility, and sovereign debt rating.
 - Bilateral: Export/import shares and distance.
 - Dummies: Own country ("home bias"), year, and US issuance interacted with year ("specialness").
- Identification.
 - Asset characteristics and quantities are exogenous (in the spirit of endowment economies).
 - Demand depends directly on own characteristics and indirectly on characteristics of other assets through price.
 - IV: Nonlinear function of all asset characteristics through market clearing.
- Estimating equations:
 - Substitution within asset class.

$$\log\left(\frac{w_{i,t}(n|l)}{w_{i,t}(0|l)}\right) = \beta_l \mu_{i,t}(n,l) + \gamma'_l \mathbf{x}_{i,t}(n,l) + \epsilon_{i,t}(n,l)$$

- Substitution across asset classes.

$$\log\left(\frac{w_{i,t}(l)}{w_{i,t}(3)}\right) = -\lambda_l \log(w_{i,t}(0|l)) + \lambda_3 \log(w_{i,t}(0|3)) + \alpha_l + \xi_{i,t}(l)$$

	Short-term	Long-term	
Variable	debt	debt	Equity
Expected return	31.53	9.31	4.29
	(5.55)	(0.61)	(0.46)
Log GDP	0.96	0.87	0.80
	(0.04)	(0.01)	(0.01)
Log GDP per capita	1.79	1.42	0.44
	(0.15)	(0.04)	(0.03)
Inflation	-0.51	-0.22	-0.02
	(0.09)	(0.02)	(0.01)
Volatility	-3.78	-1.83	-4.83
	(0.47)	(0.23)	(0.27)
Rating	0.11	0.23	0.08
	(0.02)	(0.02)	(0.01)
Export share	0.35	0.29	0.32
	(0.04)	(0.02)	(0.02)
Import share	-0.03	0.09	0.09
	(0.04)	(0.02)	(0.02)
Distance	-0.20	-0.17	-0.11
	(0.02)	(0.00)	(0.00)
Dummy: Own country			7.21
			(0.13)
Observations	17,293	31,252	30,202
R^2	0.25	0.44	0.66

Estimated demand within asset class.

Estimated demand across asset classes.

Variable	Symbol	Estimate
Log outside asset weight	t:	
Short-term debt	λ_1	0.23
		(0.06)
Long-term debt	λ_2	0.24
		(0.08)
Equity	λ_3	0.50
		(0.03)
Dummy:		
Short-term debt	$lpha_1$	-2.21
		(0.25)
Long-term debt	$lpha_2$	0.52
		(0.27)
Observations		2,339

Decomposition of exchange rates and asset prices.

• Market clearing defines an implicit function for exchange rates and asset prices.

$$\begin{bmatrix} \mathbf{e}_t \\ \mathbf{p}_t(2) \\ \mathbf{p}_t(3) \end{bmatrix} = g(\mathbf{x}_t, \mathbf{z}_t, \mathbf{p}_t(1), \mathbf{Q}_t, \epsilon_t, \xi_t)$$

- Decompose annual changes into
 - 1. Macro variables (including equity quantities).
 - 2. Short-term rates.
 - 3. Debt quantities.
 - 4. Reserves.
 - 5. Latent demand.

	Exchange	Long-term	
Variable	rate	debt	Equity
Macro variables	0.26	0.16	0.57
	(0.07)	(0.09)	(0.08)
Short-term rates	0.08	0.09	0.06
	(0.05)	(0.03)	(0.07)
Debt quantities	0.02	0.20	0.03
	(0.01)	(0.02)	(0.00)
Reserves	0.19	0.11	0.03
	(0.04)	(0.03)	(0.01)
Latent demand	0.45	0.43	0.31
	(0.04)	(0.06)	(0.06)
North America	0.08	0.05	0.06
	(0.02)	(0.01)	(0.04)
Europe	0.08	0.28	0.13
	(0.02)	(0.03)	(0.03)
Pacific	0.03	0.04	0.11
	(0.01)	(0.01)	(0.04)
Offshore financial centers	0.25	0.05	-0.01
	(0.02)	(0.02)	(0.01)
Emerging markets	0.01	0.01	0.03
	(0.00)	(0.00)	(0.03)
Other countries	0.01	0.00	0.00
	(0.00)	(0.00)	(0.01)
Observations	375	540	540

Variance decomposition of exchange rates and asset prices.

Variance decomposition of exchange rates.

- Fundamentals account for 55% of variation in exchange rates.
 - Macro variables: 26%.
 - Short-term rates: 8%.
 - Debt quantities: 2%.
 - Reserves: 19%.
- Latent demand accounts for 45%.
 - Offshore financial centers substituting within short-term debt: 26%.
 - North American investors substituting across asset classes:
 8%.
 - European investors substituting across asset classes: 8%.

Debt dynamics in Europe and the US.

- What explains the long-term yield spread between
 - Germany and the US?
 - Southern euro and Germany?
- Variance decomposition of long-term yield spreads:

	Germany	Southern euro
Variable	-US	– Germany
Macro variables	-0.02	0.64
	(0.24)	(0.13)
Short-term rates	0.53	0.00
	(0.16)	(0.00)
Debt quantities	0.15	0.14
	(0.06)	(0.04)
Reserves	0.20	0.04
	(0.20)	(0.03)
Latent demand	0.14	0.19
	(0.12)	(0.12)
North America	-0.02	0.01
	(0.03)	(0.01)
Europe	0.04	0.13
	(0.07)	(0.08)
Pacific	0.02	0.01
	(0.05)	(0.00)
Offshore financial centers	0.07	0.04
	(0.10)	(0.02)
Emerging markets	0.00	0.00
	(0.01)	(0.00)
Other countries	0.01	-0.01
	(0.01)	(0.01)
Observations	15	45

Long-term yield spread between Germany and the US



Change in the long-term yield spread between southern euro countries and Germany



- The spread between Germany and Greece is well explained by fundamentals.
- The spread between either Italy or Portugal and Germany is not. Their increase, and subsequent decline, is driven by latent demand.
- But the earlier variance decomposition shows that most of the variation in latent demand is from other European countries.
- This illustrates how demand systems can be useful to provide a narrative around market developments.

Convenience yield on US long-term debt.

- Special status of the US dollar as reserve currency.
- In the demand system, fixed effects for US issuance interacted with year.
- Estimate the convenience yield on the US dollar, long-term debt, and equity.

	Exchange	Long-term	
Investor	rate	debt	Fauity
	Tate	ucot	Equity
Total	1.28	2.15	1.70
	(0.40)	(0.14)	(0.15)
Reserves	0.06	0.48	-0.07
	(0.14)	(0.02)	(0.01)
North America	0.04	0.02	0.21
	(0.00)	(0.00)	(0.02)
Europe	0.35	0.51	0.69
	(0.06)	(0.03)	(0.04)
Pacific	0.41	0.52	0.37
	(0.06)	(0.05)	(0.03)
Offshore financial centers	0.33	0.53	0.38
	(0.15)	(0.05)	(0.05)
Emerging markets	0.07	0.05	0.09
	(0.01)	(0.01)	(0.02)
Other countries	0.03	0.04	0.03
	(0.01)	(0.00)	(0.00)

• Average convenience yield on US assets.



• The time-series dynamics of the long-term yield in the US: