Are big banks too-big-to-fail? An investigation into the size premium and scale economies for European banks

Maryam Hasannasab*, Dimitris Margaritis*, Maria Psillaki**

*University of Auckland and **University of Piraeus

TBTF Implicit Guarantees

- Large financial institutions are highly complex and highly interconnected and have been known to enjoy implicit government guarantees such as government support to prevent their failure.
- Such implicit guarantees are likely to incentivize moral hazard, distorting scale (e.g. banks getting too big) and risk choices (e.g. banks may care less about downside risk) as evident from the overambitious expansion of their balance sheets in the lead up to the GFC.
- Since governments are effectively subsidizing downside risk, the banks that enjoy TBTF status are likely to have artificially lower costs of capital, hence the link from TBTF to the cost of capital.
- Size-related diversification may reduce bank-specific risk and hence lower stock return volatility; however, this idiosyncratic risk is in essence being transcended into systematic risk, explaining why large banks may have larger market betas than smaller banks as we show later.

TBTF Implicit Guarantees

THE UNIVERSITY OF AUCKLAND
Te Whare Wānanga o Tāmaki Makaurau
NEW ZEALAND

- At best, these implicit subsidies are simply a transfer from taxpayers to bank investors. At worst, these lower financing costs create incentives for banks to either take on more risk or grow beyond their optimal scale.
- Several studies (e.g. Gandhi & Lustig, JF 2015, Kelly et al. AER 2016) have documented "Too Big to Fail" subsidies, often by comparing the cost of capital for large banks against small banks, or large banks against large corporates.
- We find that average alphas (risk adjusted returns) for decile portfolios of small banks are significantly larger than for large banks suggesting that large banks may enjoy TBTF implicit guarantees.

	Panel A: Market Cap Deciles 2000:2-2023:3										
	Small	2	3	4	5	6	7	8	9	Large	10-1
MKT_RF	0.232***	0.328***	0.41***	0.321***	0.405***	0.517***	0.644***	0.778***	0.975***	1.026***	0.797***
SMB	0.605***	0.65***	0.638***	0.543***	0.37***	0.476***	0.257**	0.212	0.048	-0.215	-0.809***
HML	0.21***	0.329***	0.396***	0.286***	0.319***	0.384***	0.518***	0.986***	0.849***	1.035***	0.814***
EURB_SP	-0.642	-1.261**	0.027	-0.5	-0.269	0.139	0.255	0.86	1.435**	1.069	1.733**
EURO_HY	-1.731***	-1.786***	-0.755	-1.222**	-0.059	-0.695	-1.088	-1.796**	-1.029	-0.608	1.152
C	1.113***	1.439***	0.321	0.753*	0.15	0.451	0.522	0.16	-0.551	-1.058*	-2.318***
Adj-Rsq	0.304	0.429	0.487	0.399	0.537	0.605	0.591	0.620	0.712	0.708	0.550
	Panel B: Market Cap Deciles 2012:1-2023:3										
	Small	2	3	4	5	6	7	8	9	Large	10-1
MKT_RF	0.295***	0.372***	0.454***	0.377***	0.451***	0.516***	0.699***	0.692***	0.938***	1.025***	0.731***
SMB	0.463***	0.385***	0.686***	0.583***	0.37***	0.623***	0.266*	0.073	0.198	0.084	-0.37
HML	0.231**	0.377***	0.461***	0.305***	0.346***	0.421***	0.612***	1.455***	0.971***	1.287***	1.06***
EURB_SP	-0.477	-2.015**	-0.146	0.595	-0.119	0.498	0.564	0.106	0.306	1.005	1.325
EURO_HY	-2.834	-0.652	-1.759	-7.789***	-2.617	-3.585	-6.32**	0.023	1.319	-1.602	1.628
C	1.732*	1.290*	1.036	2.789***	1.156	1.458*	2.338***	0.41	-0.678	-0.158	-2.037***
Adj-Rsq	0.292	0.454	0.561	0.464	0.570	0.658	0.732	0.672	0.755	0.780	0.593

Risk adjusted returns

- Estimated portfolio alphas decline roughly monotonically from decile 1 to 10. A long-short position loses 2.32% on average each period over the entire sample which is significant at the 1% level. We obtain similar results for the post GFC period.
- The market beta increases monotonically with bank size. Over the entire sample, the portfolio of large banks has a market beta of 1.026, as compared to a beta of 0.232 for a portfolio of the smallest banks.
- The loadings on SMB and HML also depend systematically on bank size. Over the entire sample the loadings on SMB decrease from 0.605 in the first size decile to -0.215 in the tenth decile.
- The loadings on HML increase from 0.231 in the first decile portfolio to 1.287 in the tenth portfolio.

The Size Factor

- The size anomaly in the empirical findings is quite robust to either using market capitalisation or book value to form decile portfolios as well as using either equally weighted or value weighted portfolio returns.
- We address this anomaly by introducing a bank-specific size factor using principal component analysis on risk adjusted returns (i.e. the monthly residuals of the size-adjusted decile portfolio regressions)
- The first principal component is interpreted as a banking industry (level) factor with roughly equal loadings on all 10 decile portfolios.
- The second principal component is clearly a candidate for the size factor with positive loadings on smaller banks monotonically decreasing towards negative loadings on larger banks.
- We then proceed to construct a size factor by multiplying the $(T \times 10)$ matrix of returns for each of the size-sorted portfolios of banks times the (10×1) loading of the second principal component.

Principal Components

The normalised PC2 loadings indicate that a highly levered portfolio can be formed with a long position of €202 in small banks and a short position of €169 in large banks. The return on this portfolio has a monthly standard deviation of 7.30%.

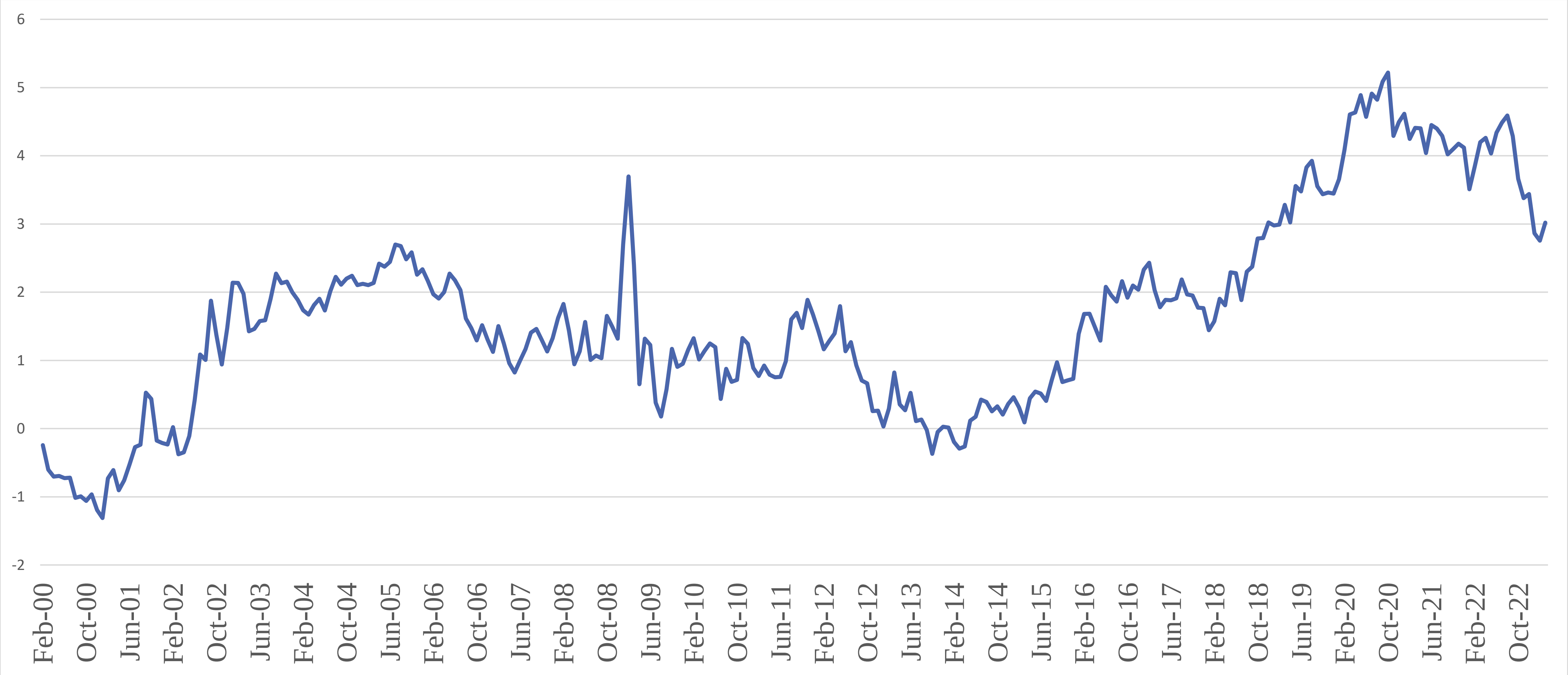
$PC1$	**0.227**	**0.262**	**0.315**	**0.345**	**0.350**	**0.341**	**0.337**	**0.306**	**0.333**	**0.324**
$PC2$	0.392	0.448	0.303	0.307	0.160	-0.135	-0.297	-0.282	-0.376	-0.327
$\widehat{PC}2$	2.022	2.314	1.565	1.584	0.829	-0.696	-1.534	-1.454	-1.940	-1.691

	Market Cap 2000-2023										
	Small	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Large**	**10-1**
MKT_RF	0.41***	0.538***	0.528***	0.431***	0.428***	0.409***	0.398***	0.462***	0.618***	0.67***	0.262***
SMB	0.388***	0.394***	0.495***	0.409***	0.343***	0.607***	0.557***	0.597***	0.484***	0.219*	-0.158
HML	0.382***	0.532***	0.509***	0.393***	0.341***	0.28***	0.28***	0.682***	0.504***	0.692***	0.298***
EBR	-0.056	-0.571	0.412	-0.139	-0.196	-0.214	-0.553	-0.176	0.26	-0.101	-0.024
HY	-1.545***	-1.567***	-0.633	-1.107*	-0.036	-0.807	-1.345**	-2.125***	-1.402**	-0.979	0.595
R[PC]	0.052***	0.061***	0.034***	0.032***	0.007	-0.031***	-0.072***	-0.092***	-0.104***	-0.104***	-0.156***
C	0.633*	0.874**	0.006	0.457	0.09	0.74**	1.184***	1.009**	0.411	-0.1	-0.88**
Adj-Rsq	0.412	0.552	0.522	0.437	0.537	0.634	0.692	0.716	0.825	0.802	0.806
	Market Cap 2012-2023										
	Small	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Large**	**10-1**
MKT_RF	0.484***	0.586***	0.55***	0.52***	0.484***	0.504***	0.572***	0.451***	0.656***	0.746***	0.263***
SMB	0.283*	0.181	0.595***	0.448***	0.339***	0.635***	0.387***	0.303	0.467***	0.349**	0.075
HML	0.532***	0.718***	0.614***	0.532***	0.397***	0.4***	0.41***	1.071***	0.521***	0.844***	0.315***
EBR	0.048	-1.419*	0.121	0.991	-0.029	0.462	0.211	-0.565	-0.478	0.231	0.025
HY	-1.959	0.34	-1.315	-7.131**	-2.467	-3.644	-6.909***	-1.095	0.013	-2.891	-0.538
R[PC]	0.066***	0.075***	0.034**	0.05***	0.011	-0.004	-0.045***	-0.085***	-0.099***	-0.098***	-0.164***
C	1.059	0.526	0.694	2.282**	1.041	1.503*	2.792***	1.271	0.328	0.834	-0.369
Adj-Rsq	0.401	0.587	0.580	0.515	0.570	0.656	0.757	0.715	0.828	0.831	0.796

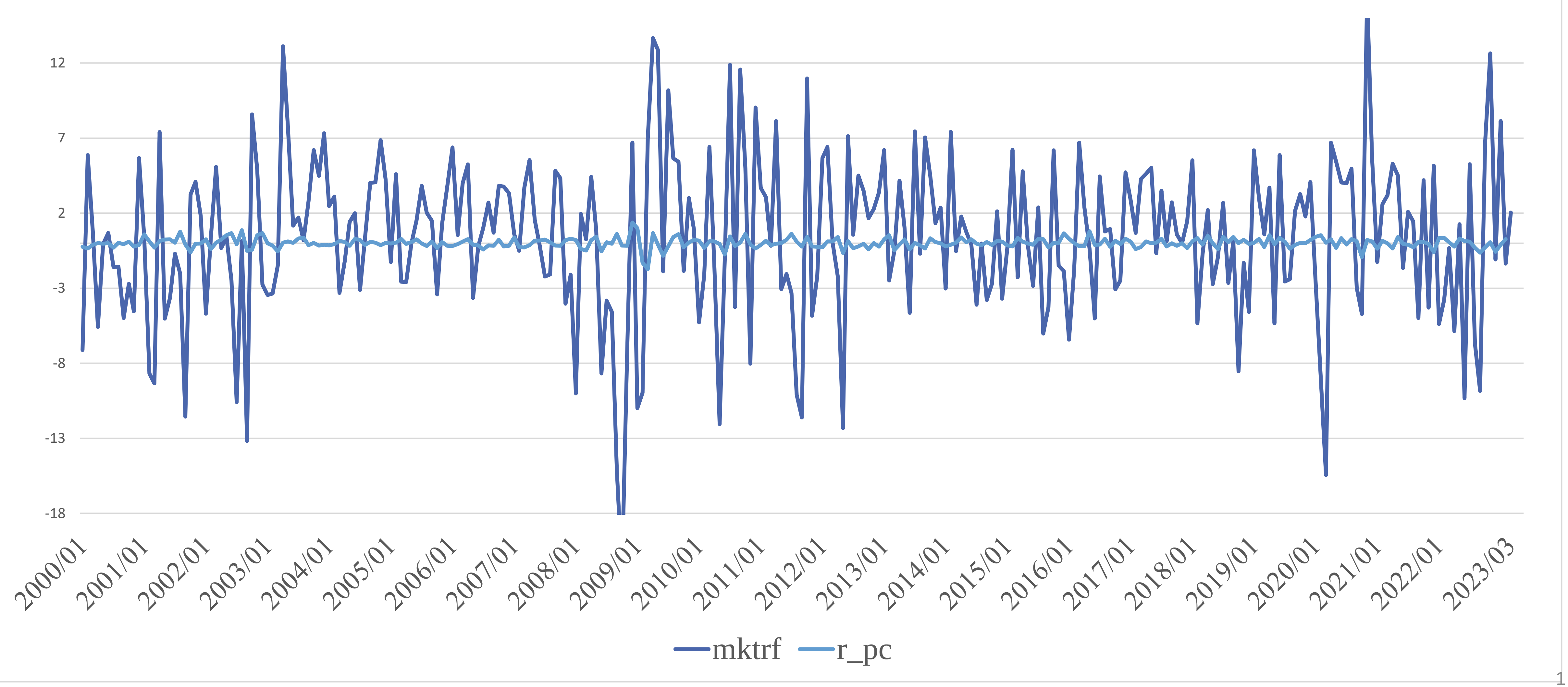
Size Factor

- The results reported in the Table show remaining evidence of risk-adjusted excess returns (portfolio alphas) across deciles in Panel A for the entire sample.
- A long-short position that goes long on large banks in decile 10 and short on small banks in decile 1 loses 0.88% over the entire sample.
- While this spread is statistically significant, it is much smaller than the spread reported in Table 1.
- We do not find evidence that the spread is significant in Panel B for the post GFC/ Sovereign Crisis sample.
- The question is whether an RTS adjustment can reconcile further the anomaly. We turn next to examine the importance of returns to scale in the pricing relationship.

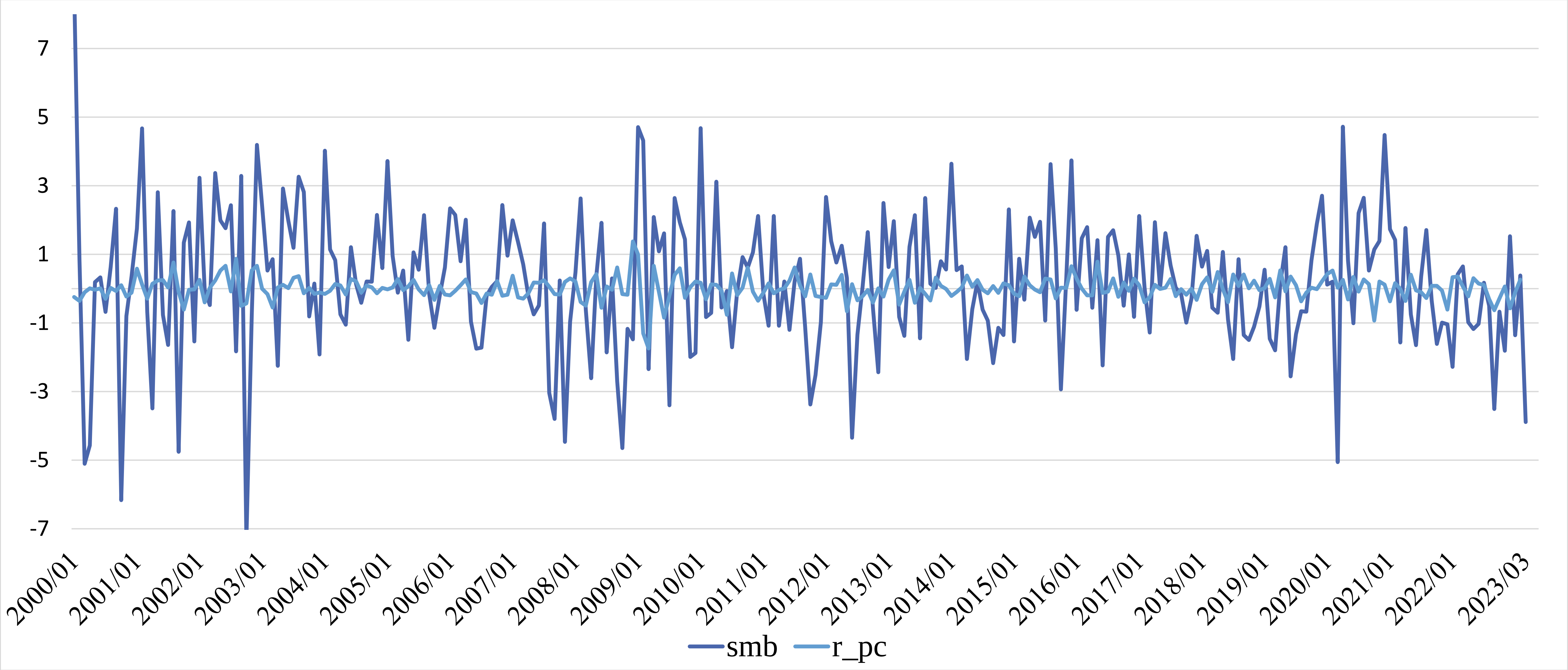
Risk-adjusted cum return on a portfolio that is long small banks and short large banks



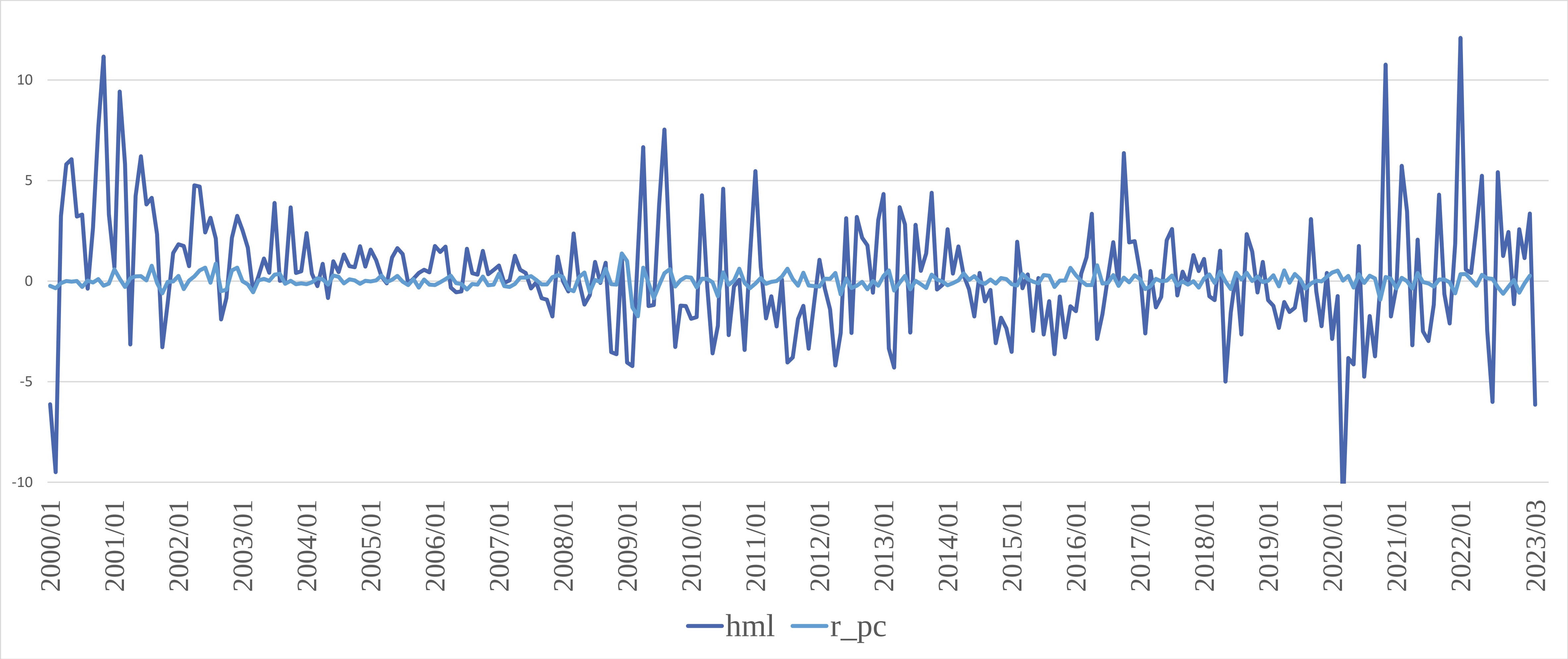
Market and Size Factors



SMB and SIZE Factors



HML and SIZE Factors



Economies of Scale

- We use a new method to estimate returns to scale (RTS) for European banks based on closeness to most productive scale size benchmark.
- We then sort banks first on size and then on RTS to examine whether differences in risk adjusted returns between small and large banks reflect the advantages of more productive size.
- The first question we ask is if large banks have lower expected returns than small banks because they enjoy economies of scale.

Scale Elasticity: Issues

A major challenge to overcome is to obtain a reliable measure of returns to scale (RTS).

- Parametric methods provide the flexibility of smooth functional forms which are readily differentiable, but concerns arise about:

- estimated models that may not satisfy the underlying technology regularity conditions especially those which are in the form of inequality restrictions; or
- the direction of the projections of inefficient points to the frontier where SE is evaluated.

- Non-parametric methods such as DEA typically render interval rather than point estimates of SE with intervals often being too large to be informative.

- DEA based methods offer many advantages but have a major problem, namely wide intervals of SE, how do we then get into a single value estimate??

Data Envelopment Analysis

$$\mathcal{T} = \{(\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{R}^{m+s}_{\geq 0} | \quad \boldsymbol{y} \text{ can be produced by } \quad \boldsymbol{x}\}.$$

$$\mathcal{T}_{VRS} = \left\{(\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{R}^{m+s}_{\geq 0} \middle| \boldsymbol{x} \geq \sum_{j=1}^{n} \lambda^j \boldsymbol{x}^j,\ \boldsymbol{y} \leq \sum_{j=1}^{n} \lambda^j \boldsymbol{y}^j,\ \sum_{j=1}^{n} \lambda_j = 1, \lambda^j \geq 0, j = 1, \dots, n\right\}.$$

$(\boldsymbol{x}^j, \boldsymbol{y}^j)^T, j = 1, \dots, n,$ denotes the input-output vector of the j^{th} firm/bank, generically referred to as a Decision-Making Unit (DMU) in the DEA terminology.

$$D_i(\boldsymbol{x}^o, \boldsymbol{y}^o) = \theta^* = min\{\theta : (\theta \boldsymbol{x}^o, \boldsymbol{y}^o) \in \mathcal{T}_{VRS}\}$$

$$D_i(\boldsymbol{x}^o, \boldsymbol{y}^o) = \max_{\boldsymbol{u},\boldsymbol{v},u_o} \boldsymbol{u}^T \boldsymbol{y}^o + u_o$$

s.t. $\quad \boldsymbol{u}^T \boldsymbol{y}^j - \boldsymbol{v}^T \boldsymbol{x}^j + u_o \leq 0, \quad$ j=1,…,n,

$$\boldsymbol{v}^T \boldsymbol{x}^o = 1,$$

$$(\boldsymbol{u}, \boldsymbol{v}) \geq \boldsymbol{0}.$$

$$D_o(\boldsymbol{x}^o, \boldsymbol{y}^o) = \phi^* = max\{\phi : (\boldsymbol{x}^o, \phi \boldsymbol{y}^o) \in \mathcal{T}_{VRS}\}$$

$$D_o(\boldsymbol{x}^o, \boldsymbol{y}^o) = \min_{\boldsymbol{u},\boldsymbol{v},u_o} \boldsymbol{v}^T \boldsymbol{x}^o - u_o$$

s.t. $\quad \boldsymbol{u}^T \boldsymbol{y}^j - \boldsymbol{v}^T \boldsymbol{x}^j + u_o \leq 0, \quad$ j=1,…,n,

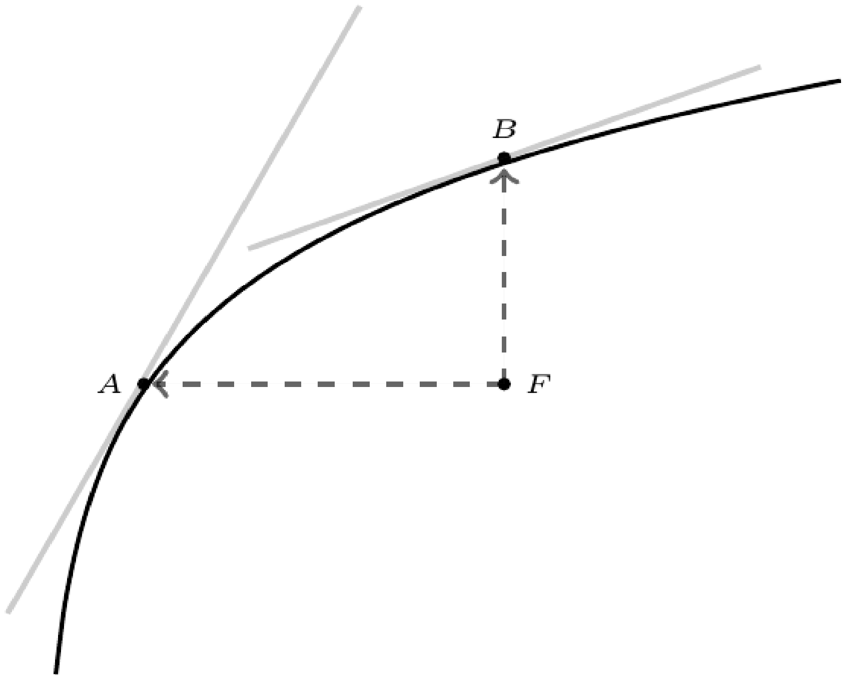
$$\boldsymbol{u}^T \boldsymbol{y}^o = 1,$$

$$(\boldsymbol{u}, \boldsymbol{v}) \geq \boldsymbol{0},$$

SCALE ELASTICITY

$$D(\boldsymbol{x},\boldsymbol{y}) = \bar{\mathbf{u}}^T\boldsymbol{y} - \bar{\mathbf{v}}^T\boldsymbol{x} + u_o = 0$$

$$\mathcal{E}(\boldsymbol{x}^o,\boldsymbol{y}^o) = \frac{-\sum_{i=1}^{m}\frac{\partial D(\boldsymbol{x},\boldsymbol{y})}{\partial x_i}x_i}{\sum_{r=1}^{m}\frac{\partial D(\boldsymbol{x},\boldsymbol{y})}{\partial y_r}y_r}\Big|_{(\boldsymbol{x}^o,\boldsymbol{y}^o)} = \frac{-\nabla_x D(\boldsymbol{x},\boldsymbol{y}).\boldsymbol{x}}{\nabla_y D(\boldsymbol{x},\boldsymbol{y}).\boldsymbol{y}}\Big|_{(\boldsymbol{x}^o,\boldsymbol{y}^o)} = \frac{\bar{\mathbf{v}}^T\boldsymbol{x}^o}{\bar{\mathbf{u}}^T\boldsymbol{y}^o}$$



MPSS

The concept of MPSS introduced by Banker (1984) plays a pivotal role in our approach. MPSS is an optimal scale size in the sense that efficient firms not operating under local CRS will be able to improve their productivity by changing their size to the point where CRS holds.

IDEA:

For efficient points: Choosing the part of the frontier which is as close as possible to the MPSS part of the frontier

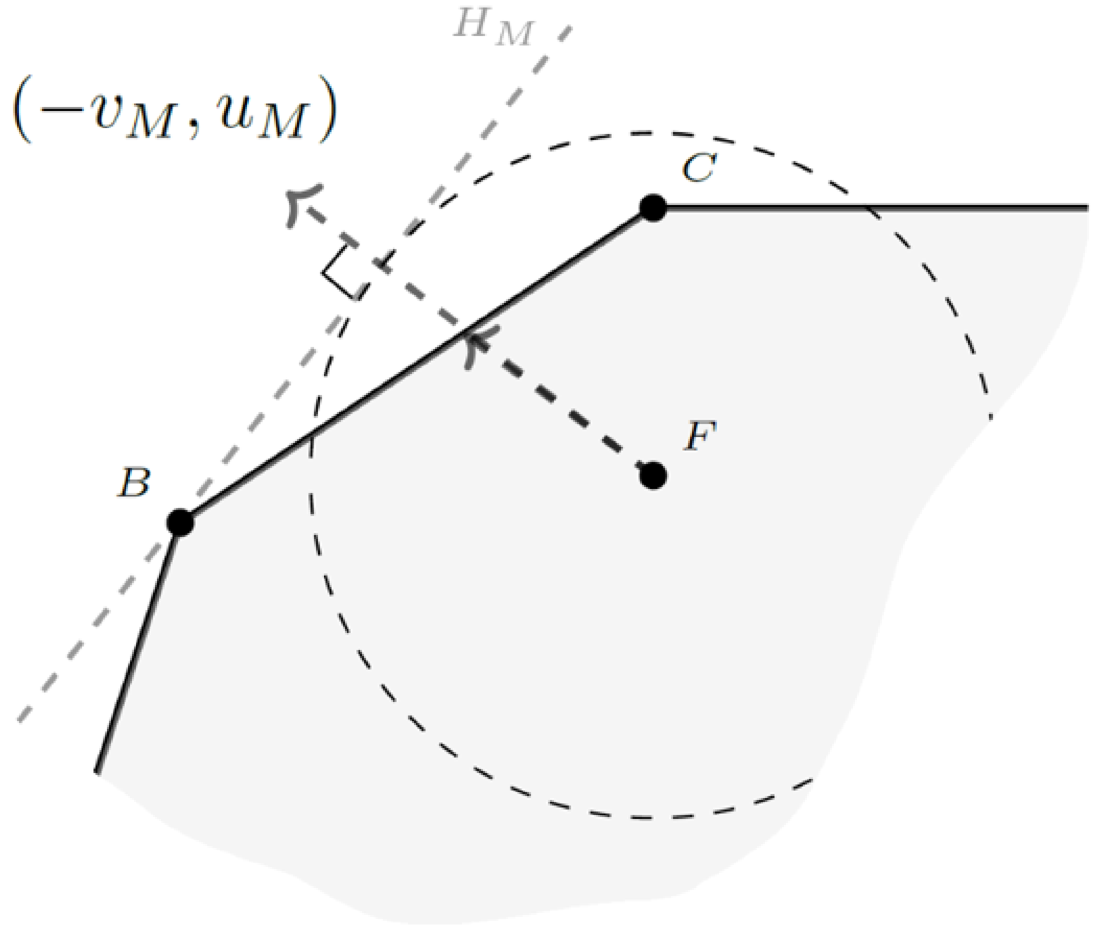
For inefficient point: Moving toward the MPSS frontier but how??

Which direction and how?

- The smart thing here is to use a direction that also captures relative prices hence achieving efficiency (optimal input-output mix). The allocative efficiency issue is important as it is often identified as a shortcoming of production-based asset pricing.

- Price uncertainties are common economy-wide shocks that affect each firm differently depending on its input-output mix. And as operating leverage increases and the wedge between factor mix and price widens, firm's risk rises.

Inefficient Banks



$$\min_{\boldsymbol{x},\boldsymbol{y}\boldsymbol{\lambda},\boldsymbol{d}} \|(\boldsymbol{x}^o - \boldsymbol{x}, \boldsymbol{y}^o - \boldsymbol{y})\|_2$$

$$\sum_{j=1}^{n} \lambda^j \boldsymbol{x}^j = \boldsymbol{x},$$

$$\sum_{j=1}^{n} \lambda^j \boldsymbol{y}^j = \boldsymbol{y},$$

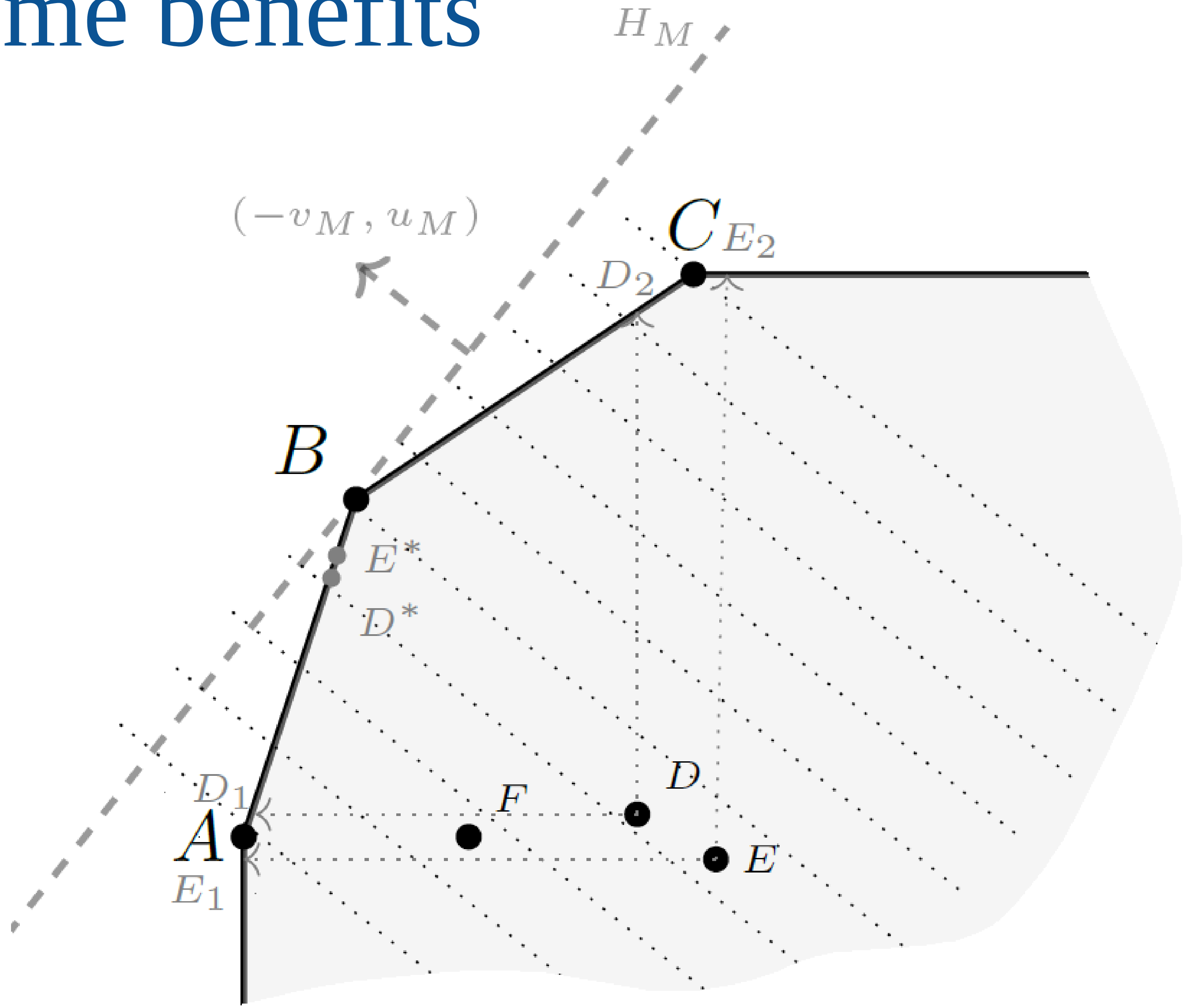
$$\lambda^j \geq 0, \qquad j = 1, \dots, n,$$

$$\boldsymbol{u}^T \boldsymbol{y}^j - \boldsymbol{v}^T \boldsymbol{x}^j + d_j = 0, \qquad j = 1, \dots, n,$$

$$\lambda^j d_j = 0, \qquad j = 1, \dots, n,$$

$$\boldsymbol{u} \geq \boldsymbol{1}, \boldsymbol{v} \geq \boldsymbol{1},$$

Some benefits



$$\max_{\boldsymbol{u},\boldsymbol{v},u_o,\rho} \ \rho$$

$$\boldsymbol{u}^T\boldsymbol{y}^j - \boldsymbol{v}^T\boldsymbol{x}^j + u_o \le 0, \qquad j = 1, \ldots, n-1,$$

$$\mathbf{u}^T\boldsymbol{y}^o - \mathbf{v}^T\boldsymbol{x}^o + u_o = 0,$$

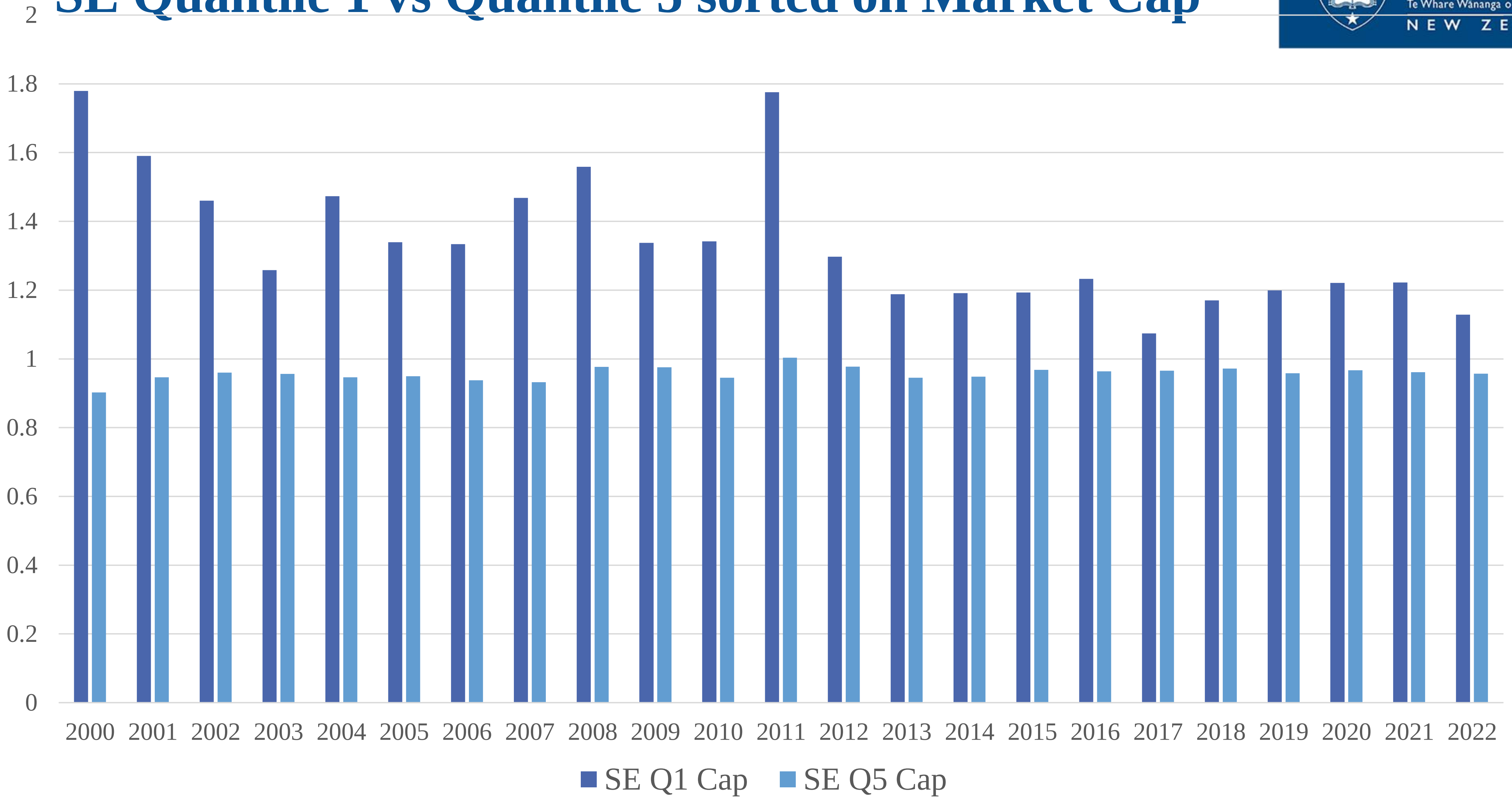
$$\rho \le \boldsymbol{v}^T\boldsymbol{x}^{\boldsymbol{o}} \le 1,$$

$$\rho \le \boldsymbol{u}^T\boldsymbol{y}^o \le 1,$$

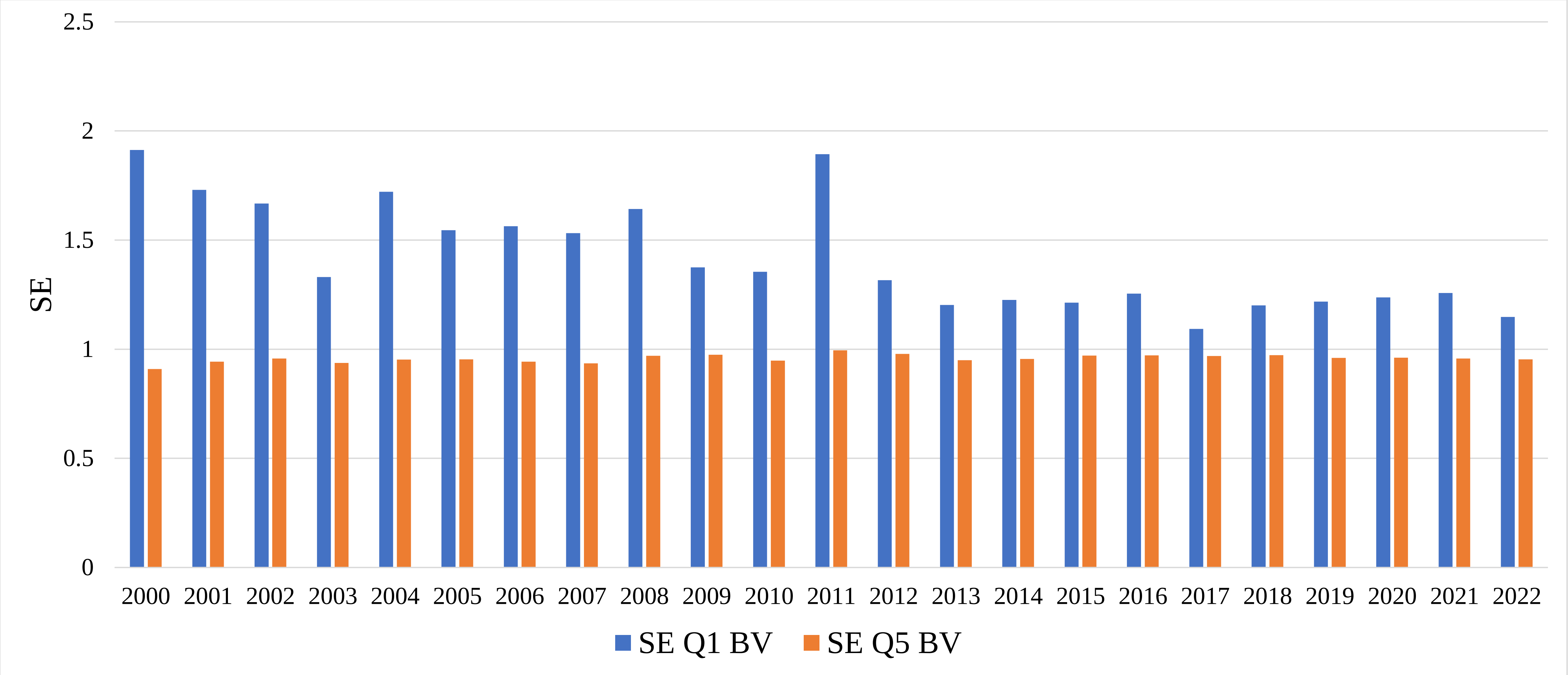
$$\boldsymbol{v} \ge 0, \boldsymbol{u} \ge 0.$$

At any efficient point of $\mathcal{T}_{VRS}$, SE equals the optimal value of or its reciprocal, i.e., SE=ρ^* or SE=1/ρ^*.

SE Quantile 1 vs Quantile 5 sorted on Market Cap



SE Quantile 1 vs Quantile 5 sorted on Total Assets



SE across Total Assets and Market Cap Quantiles

2000-2007							
Total Assets Q.				Market cap Q.			
BV Q.	mean	median	stdev	MC Q.	Mean	median	stdev
1	1.620	1.446	0.617	1	1.466	1.364	0.491
2	1.057	1.027	0.105	2	1.071	1.016	0.172
3	1.002	1.006	0.024	3	1.032	1.007	0.191
4	0.990	1.000	0.035	4	0.989	1.000	0.052
5	0.942	1.000	0.112	5	0.942	1.000	0.112
2008-2011							
1	1.566	1.366	0.632	1	1.51	1.276	0.637
2	1.037	1.021	0.115	2	1.098	1.010	0.275
3	0.999	1.006	0.025	3	0.987	1.003	0.098
4	0.983	1	0.084	4	0.99	1.000	0.030
5	0.972	0.999	0.154	5	0.975	1.000	0.160
2012-2023							
1	1.208	1.084	0.389	1	1.191	1.058	0.396
2	1.001	1.001	0.041	2	1.007	1.000	0.048
3	0.995	1	0.015	3	0.995	1.000	0.031
4	0.99	1	0.022	4	0.99	1.000	0.025
5	0.963	0.999	0.072	5	0.963	0.999	0.074

Panel A Market Cap-SE Portfolio Sorts (25 50 25)										
	Small			Medium			Large			
	DRS	CRS	IRS	DRS	CRS	IRS	DRS	CRS	IRS	9-1
MKT_RF	0.459***	0.425***	0.335***	0.602***	0.54***	0.455***	0.9***	0.908***	0.851***	0.562***
SMB	0.407**	0.498***	0.602***	0.459***	0.412***	0.467***	-0.013	0.077	-0.409*	-1.266***
HML	0.304**	0.104	0.224***	0.547***	0.62***	0.433***	1.321***	1.071***	1.268***	0.766***
EBR	-0.170	-0.434	-0.596	0.496	-0.074	-0.336	0.84	-0.046	0.873	1.887
HY	-0.096	-0.061	-0.123***	-0.138**	-0.072	-0.009	-0.021	0.058	0.298**	0.375*
C	0.404	0.29	1.036***	0.266	0.557	0.348	-0.81	-0.624	-1.896**	-2.589**
Adj-Rsq	0.188	0.231	0.454	0.706	0.668	0.647	0.766	0.739	0.547	0.222

Panel B Market Cap-SE Portfolio Sorts (25 50 25)										
	Small			Medium			Large			
	DRS	CRS	IRS	DRS	CRS	IRS	DRS	CRS	IRS	9-1
MKT_RF	0.583***	0.596***	0.507***	0.556***	0.463***	0.464***	0.66***	0.663***	0.569***	0.022
SMB	0.248	0.286*	0.388***	0.534***	0.536***	0.451***	0.378***	0.475***	0.051	-0.345
HML	0.414***	0.256**	0.386***	0.456***	0.47***	0.451***	0.848***	0.589***	0.712***	-0.233
EBR	0.243	0.138	-0.014	0.36	-0.301	-0.308	0.126	-0.774	0.033	0.48
HY	-0.084	-0.046	-0.109***	-0.151**	-0.093	-0.006	-0.089	-0.011	0.218*	0.226
R_PC	0.035**	0.048***	0.05***	-0.017**	-0.028***	0.003	-0.088***	-0.089***	-0.103***	-0.187***
C	0.075	-0.157	0.576*	0.414	0.804**	0.317	-0.032	0.169	-0.98	-0.996
Adj-Rsq	0.201	0.276	0.558	0.710	0.683	0.645	0.828	0.811	0.618	0.414

- The results show a negative and significant risk-adjusted premium for large IRS banks in Panel A but not in Panel B after we control for the bank ‘size’ factor.
- In contrast small IRS banks have a positive and significant risk-adjusted premium in both panels.
- We obtain similar results using the book value of assets with large IRS banks still commanding a negative and significant risk premium after controlling for the size factor whereas the small IRS banks have again positive and significant risk-adjusted returns.

THE UNIVERSITY OF AUCKLAND
Te Whare Wānanga o Tāmaki Makaurau
NEW ZEALAND

- In contrast there is no evidence that large CRS and DRS banks exhibit positive and significant risk-adjusted returns.
- Overall, our findings indicate that there is some albeit not conclusive evidence that excess return differences between small and large banks may reflect RTS, specifically for IRS banks, rather than TBTF subsidies.
- We turn next to provide further evidence using characteristics regressions.

Characteristics Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log_assets	-0.064***	-0.066***			-0.057***	-0.103***		-0.085***	-0.084***
Log_assets*IRS		0.007***							
Log_assets*DRS		-0.006**							
Log_market	0.062***	0.063***	0.056***	0.058***	0.063***	0.090***	0.111***	0.090***	0.090***
Log_market*IRS	0.004*		0.011***		0.005**	0.007*	-0.047***	-0.043***	-0.042***
Log_market*DRS	-0.006**		-0.006**		-0.006**	0.015***	0.025***	0.025***	0.023***
Log_book			-0.067***	-0.072***	-0.009		-0.122***		
Log_book*IRS				0.014***					
Log_book*DRS				0.001					
ESG							-0.001***	-0.001**	-0.001*
ESG*IRS							-0.001**		-0.001
ESG*DRS							0.001**		0.001
ESG*CRS									
IRS	-0.090*	-0.154***	-0.206***	-0.286***	-0.103**	-0.168**	1.057***	0.906***	0.896***
DRS	0.066	0.078	0.072	-0.064	0.072	-0.423***	-0.683***	-0.667***	-0.641***
NIM						-0.010***			
Constant	0.316***	0.341***	0.334***	0.401***	0.325***	0.695***	0.372***	0.218**	0.211**
Adj. R-sq	0.036	0.036	0.033	0.032	0.036	0.037	0.071	0.061	0.061

Characteristics Regressions

- The characteristics regression findings corroborate the importance of the size factor in bank returns.
- We obtain a significant negative coefficient for log_book and log_assets and a positive coefficient for log market cap indicating that an increase in book or assets value above the sample average lowers annual returns for a typical bank, holding all variables, including market capitalisation constant. These coefficients are significant at the 1% level.
- Banks with higher NIM appear to have lower expected returns. The negative and significant ESG coefficient shows that better governance attributes are also associated with lower expected returns.

Summary

- We find a size anomaly in risk adjusted bank returns suggesting implicit TBTF subsidies for large banks unless they are exploiting significant IRS
- Economies of scale couldn't entirely explain this anomaly
- Controlling for a bank specific size factor provides less evidence of significant alphas in bank returns, esp. post GFC.

THE UNIVERSITY OF AUCKLAND
Te Whare Wānanga o Tāmaki Makaurau
NEW ZEALAND

THE UNIVERSITY OF AUCKLAND
Te Whare Wānanga o Tāmaki Makaurau
NEW ZEALAND

Power Laws and bank concentration

- We turn next to study the changing role of idiosyncratic volatility and concentration as shaping forces of the bank size distribution using dynamic nonparametric power law distributions.
- Power distributions are very convenient since they characterise many regularities in economics and finance. In our case, they fully characterize the distribution of bank assets in terms of two factors (idiosyncratic volatilities and cross-section mean reversion).
- The main question of interest in our context is whether idiosyncratic volatility has diminished after new regulations, recognising that volatility affects both concentration and systemic risk, while concentration itself further affects systemic risk.

- The most common way to model power law distributions is proportional random growth, as pioneered by Gabaix (QJE 1999).
- These empirical techniques are flexible and allow us to estimate and quantify the distributional effect of idiosyncratic volatilities across every rank in the bank size distribution.
- Furthermore, these methods are robust and avoid model misspecification issues since they allow for asset growth rates and volatilities that vary across different bank characteristics including rank.
- Idiosyncratic volatility is a root cause of contagion and systemic risk emanating from networks and also a contributing factor for aggregate volatility (Acemoglu et al. 2012).
- In fact, the failure of financial institutions like Lehman Brothers or Bear Stearns often led to greater dislocation than failures in other industries.

Dynamic Power Laws

- The total assets of each bank i = 1, . . . , N in this economy are given by a process that evolves according to a stochastic differential equation where its growth rate and volatility satisfy some basic integrability conditions and require that no two banks' assets are perfectly correlated over time.
- Our analysis deviates from standard power laws based on invariance properties by making the asset size distribution to depend explicitly on bank rank.
- As such we introduce heterogeneity by allowing for different asset volatilities across banks in the model, which is more suitable for capturing the dynamics of bank size distributions.
- Our method follows the approach of Fernholz and Koch (AER 2017) characterizing the entire asset distribution in terms of two factors (1) cross-sectional mean reversion; and (2) idiosyncratic asset volatility

Bank asset concentration

$$\frac{\text{idiosyncratic volatility of bank assets}}{reversion\ rates\ of\ bank\ assets}$$

- This definition highlights the dual role of idiosyncratic bank asset volatility as both a shaping force of the bank size distribution and a determinant of financial stability.
- At each rank, the asset distribution is fully characterised by idiosyncratic volatility and mean reversion rates meaning that any increase in asset concentration must be caused in a statistical sense by either increases in idiosyncratic volatility or a decrease reversion rates.