Internet Appendix for Deep Learning in Asset Pricing*

Luyang Chen† Markus Pelger‡ Jason Zhu§

September 10, 2020

Abstract

The Internet Appendix collects multiple results that support the results in the main text. Among others it includes implementation details, the results for the benchmark approaches, additional robustness results and a detailed description of the data.

*Citation format: Chen, Luyang, Pelger, Markus and Jason Zhu, Internet Appendix for "Deep Learning in Asset Pricing".

†Stanford University, Institute for Computational and Mathematical Engineering, Email: lych@alumni.stanford.edu.
‡Stanford University, Department of Management Science & Engineering, Email: mpelger@stanford.edu.
§Stanford University, Department of Management Science & Engineering, Email: jzhu121@stanford.edu.

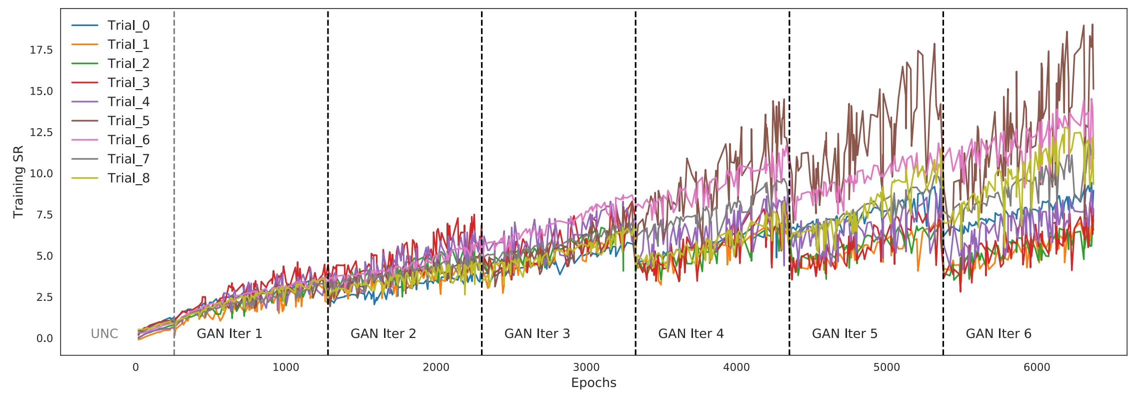
Contents

IA.A. Overview

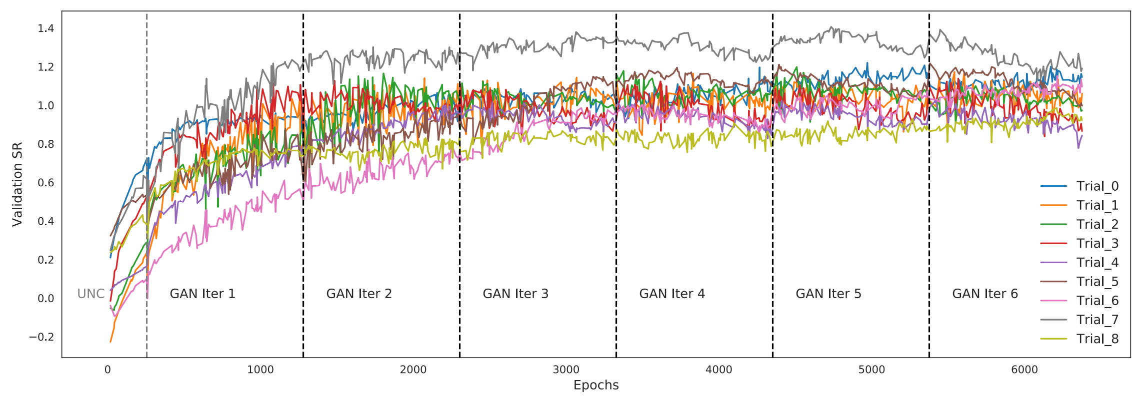
The Internet Appendix collects multiple results that support the results in the main text. Section IA.B shows the performance for multiple GAN iterations. While additional GAN iterations improve the in-sample results on the training data, the results on the validation and test data do not improve further after one GAN iteration. Section IA.C collects the additional results for the illustrative GAN example based on size, value and investment. In Section IA.D we confirm that SDF loadings are predictive for future returns and that the results for β sorted deciles portfolios hold for equally and value weighted portfolios. Section IA.E reports the structure of the SDF as a function of characteristics for FFN, EN and LS. We show that the forecasting approach FFN seems to capture less interaction effects. By construction these interaction effects are ruled out for the linear models. Section IA.F provides further results for the effect of market capitalization on the performance of machine learning investment portfolios. In Section IA.G we show that the economic structure estimated by our benchmark GAN model is robust to the tuning parameters. We collect the variable importance and functional form of the SDF for the best four models on the validation data. Section IA.H collects the detailed results for the combination of GAN with IPCA. In Section IA.I we provide the asset pricing results and functional form of the SDF for additional characteristics. Last but not least, Section IA.J describes the macroeconomic and firm-specific variables in detail.

IA.B. Empirical Implementation

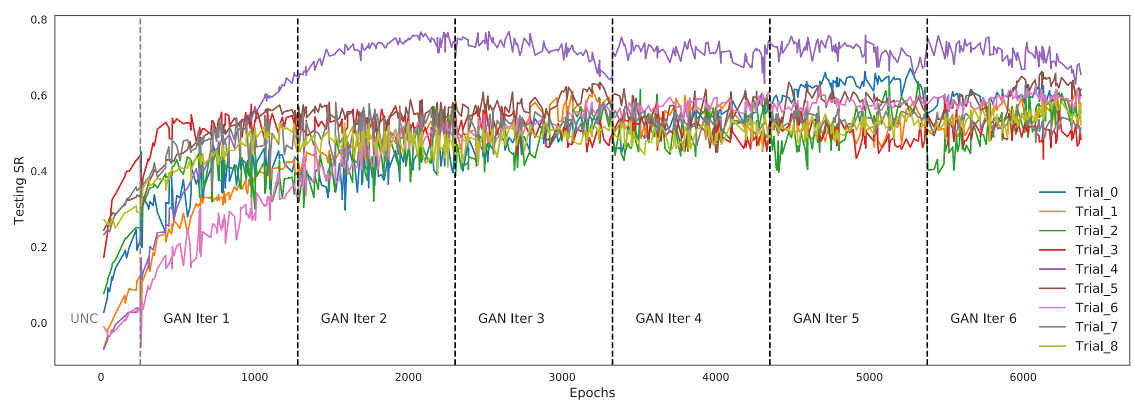
Figure IA.1: Evaluation of GAN for Different Number of GAN Iterations



(a) Training



(b) Validation



(c) Test

This figure shows the Sharpe ratio on the training, validation and test data for different number of iterations of the GAN fit for the benchmark model in our empirical analysis. The number of epochs is the number of complete passes through the training data set. The first 256 epochs are for the first stage of the unconditional GAN fit, that is, this represents the UNC fit. This is followed by 64 epochs for constructing the conditioning function g which are not counted in these plots. The next 1024 epochs fit the GAN model for the first set of moment conditions given by g. Hence, after the first 256 epochs, every 1024 epochs represent one iteration of the GAN fit. Our ensemble fit is based on 9 independent estimations of the model which are all included in the plots. Subfigure (b) shows the Sharpe ratio on the validation data. The benchmark model in the paper uses one GAN iteration, that is, we use the model represented by the second vertical line. The third vertical line corresponds to two GAN iterations which does not improve the Sharpe ratio. In contrast, the unconditional model UNC represented by the first vertical line is strictly inferior to the GAN fit.

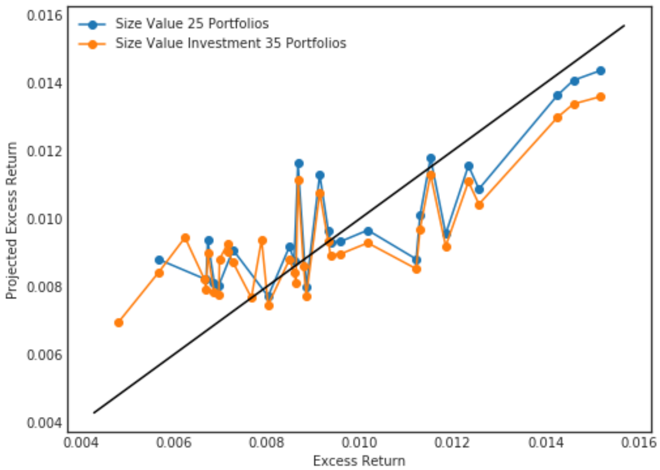
IA.C. Illustrative GAN Example

Table IA.I: Performance of Different SDF Models for Portfolio Sorts based on Size, Value and Investment

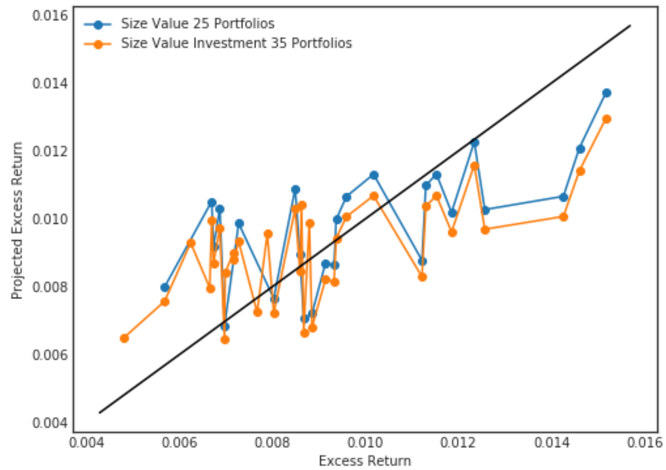
Model	SR			EV			Cross-Sectional R^2		
	Train	Valid	Test	Train	Valid	Test	Train	Valid	Test
	25 Double-Sorted Size and Value Portfolios								
UNC (SV)	0.22	0.42	0.27	0.50	0.60	0.48	0.50	0.83	0.60
UNC (SVI)	0.30	0.21	0.28	0.64	0.71	0.60	0.77	0.83	0.82
GAN (SV-SV)	0.32	0.40	0.38	0.61	0.64	0.55	0.88	0.76	0.84
GAN (SVI-SV)	0.50	0.58	0.43	0.78	0.80	0.72	0.91	0.73	0.96
GAN (SVI-SVI)	0.50	0.57	0.51	0.81	0.82	0.75	0.90	0.69	0.98
GAN	2.68	1.43	0.75	0.80	0.80	0.76	0.92	0.74	0.98
	10 Decile Investment Portfolios + 25 Double-Sorted Size and Value Portfolios								
UNC (SV)	0.22	0.42	0.27	0.52	0.64	0.48	0.45	0.88	0.60
UNC (SVI)	0.30	0.21	0.28	0.65	0.74	0.60	0.72	0.88	0.82
GAN (SV-SV)	0.32	0.40	0.38	0.63	0.68	0.57	0.85	0.80	0.86
GAN (SVI-SV)	0.50	0.58	0.43	0.76	0.80	0.70	0.87	0.77	0.96
GAN (SVI-SVI)	0.50	0.57	0.51	0.79	0.81	0.72	0.88	0.73	0.98
GAN	2.68	1.43	0.75	0.79	0.80	0.72	0.91	0.77	0.97

This table shows the monthly Sharpe ratio (SR), explained time-series variation (EV) and cross-sectional R^2 for different SDF models in the illustrative GAN example. UNC (SV) and UNC (SVI) are unconditional models with respect to the test assets, that is, they use only size and value respectively size, value and investment for the SDF weights, but set g to a constant. The GAN models use a non-trivial g. GAN (SVI-SV) allows the SDF weight ω to depend on size, value and investment, but the test asset function g to depend only on size and investment. The model labeled as GAN is our benchmark model estimated with all characteristics and macroeconomic information. We evaluate the model on 25 double-sorted size and book-to-market portfolios (SV 25) and we add another 10 decile portfolios sorted on investment (SVI 35). The portfolios are value-weighted.

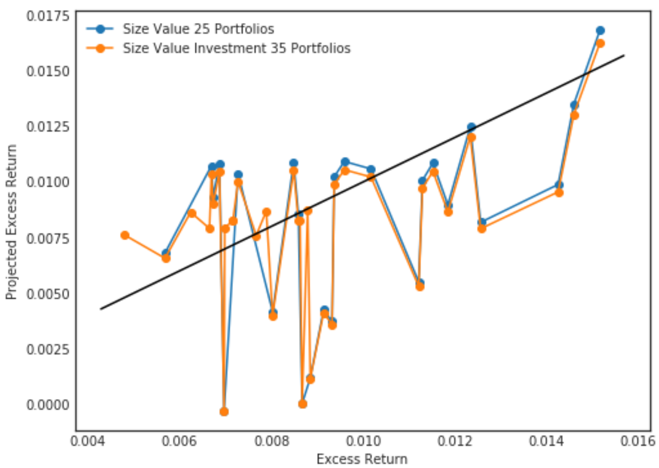
Figure IA.2: GAN Portfolio Pricing



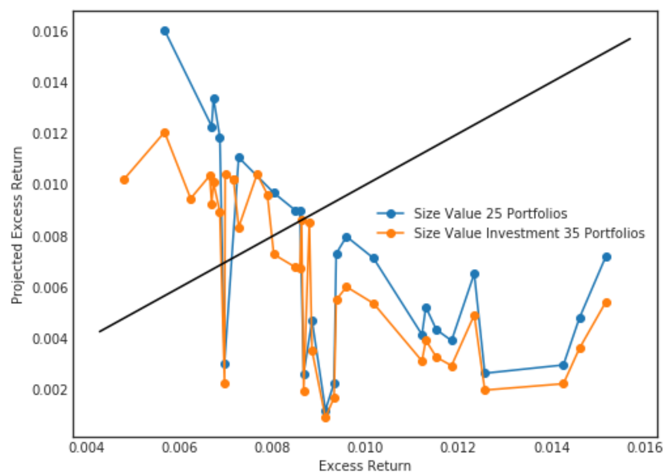
(a) GAN



(b) GAN (SVI-SV)



(c) GAN (SV-SV)



(d) UNC (SV)

This figure shows the predicted and average excess returns for the 25 and 35 sorted portfolios. The tuning parameters are chosen optimally on the validation data set and are different from the general benchmark GAN. UNC (SV) and UNC (SVI) are unconditional models with respect to the test assets, that is, they use only size and value respectively size, value and investment for the SDF weights, but set g to a constant. The GAN models use a non-trivial g. GAN (SVI-SV) allows the SDF weight ω to depend on size, value and investment, but the test asset function g to depend only on size and investment. The model labeled as GAN is our benchmark model estimated with all characteristics and macroeconomic information. We evaluate the model on 25 double-sorted size and book-to-market portfolios (SV 25) and we add another 10 decile portfolios sorted on investment (SVI 35). The portfolios are value-weighted.

Table IA.II: Explained Variation and Pricing Errors for Double-Sorted Portfolios based on Size and Value

		UNC		GAN			GAN Full	UNC		GAN			GAN Full
		SV	SVI	SV-SV	SVI-SV	SVI-SVI	GAN	SV	SVI	SV-SV	SVI-SV	SVI-SVI	GAN
LME	BEME	Explained Variation						Alpha					
1	1	0.19	0.15	-0.00	0.45	0.52	0.63	0.12	0.13	0.17	0.03	0.00	-0.06
1	2	0.12	0.32	0.34	0.62	0.67	0.74	0.16	0.11	0.10	0.01	-0.01	-0.04
1	3	0.32	0.55	0.68	0.73	0.75	0.76	0.22	0.16	0.09	0.07	0.05	0.01
1	4	0.53	0.73	0.74	0.78	0.78	0.75	0.19	0.12	0.02	0.05	0.04	0.01
1	5	0.68	0.76	0.59	0.73	0.71	0.76	0.16	0.09	-0.03	0.03	0.02	0.02
2	1	0.31	0.33	-0.03	0.60	0.70	0.68	0.08	0.07	0.14	0.00	-0.03	-0.02
2	2	0.30	0.54	0.42	0.80	0.84	0.81	0.14	0.09	0.11	0.01	-0.01	-0.01
2	3	0.37	0.76	0.79	0.88	0.89	0.86	0.20	0.10	0.09	0.05	0.04	0.03
2	4	0.56	0.83	0.87	0.88	0.88	0.85	0.14	0.05	0.01	0.00	0.00	-0.01
2	5	0.72	0.86	0.88	0.85	0.85	0.85	0.11	0.03	-0.00	0.00	0.00	0.02
3	1	0.51	0.54	0.14	0.69	0.77	0.73	0.08	0.07	0.15	0.03	0.00	0.02
3	2	0.55	0.76	0.62	0.85	0.88	0.85	0.14	0.09	0.11	0.05	0.03	0.05
3	3	0.57	0.88	0.88	0.91	0.91	0.90	0.16	0.07	0.06	0.03	0.03	0.05
3	4	0.68	0.90	0.90	0.89	0.89	0.88	0.12	0.03	0.02	0.01	0.01	0.02
3	5	0.78	0.86	0.86	0.83	0.82	0.81	0.06	-0.02	-0.01	-0.02	-0.02	0.01
4	1	0.85	0.77	0.49	0.76	0.80	0.79	-0.03	0.00	0.08	0.01	-0.01	0.01
4	2	0.90	0.88	0.84	0.85	0.85	0.85	-0.01	-0.01	0.00	-0.01	-0.01	-0.00
4	3	0.86	0.88	0.87	0.83	0.82	0.83	0.04	-0.01	-0.02	-0.01	-0.00	0.00
4	4	0.87	0.89	0.89	0.85	0.85	0.85	0.03	-0.02	-0.03	-0.02	-0.01	0.01
4	5	0.84	0.77	0.83	0.78	0.78	0.79	-0.01	-0.07	-0.05	-0.05	-0.03	-0.01
5	1	-0.94	0.33	0.57	0.50	0.50	0.44	-0.20	-0.09	-0.02	-0.05	-0.04	-0.06
5	2	0.06	0.47	0.67	0.60	0.64	0.58	-0.13	-0.09	-0.05	-0.05	-0.03	-0.05
5	3	0.53	0.45	0.62	0.56	0.63	0.57	-0.07	-0.09	-0.06	-0.05	-0.03	-0.04
5	4	0.61	0.56	0.69	0.64	0.66	0.67	-0.10	-0.11	-0.08	-0.07	-0.04	-0.02
5	5	0.47	0.29	0.58	0.52	0.56	0.56	-0.11	-0.14	-0.08	-0.08	-0.05	-0.03
		Explained Variation						Cross-Sectional R^2					
All		0.48	0.60	0.55	0.72	0.75	0.76	0.60	0.82	0.84	0.96	0.98	0.98

This table shows the out-of-sample explained variation and pricing errors for double sorted portfolios based on size (`LME`) and book-to-market ratio (`BEME`). UNC (SV) and UNC (SVI) are unconditional models with respect to the test assets, that is, they use only size and value respectively size, value and investment for the SDF weights, but set g to a constant. GAN (SVI-SV) allows the SDF weight ω to depend on size, value and investment, but the test asset function g to depend only on size and investment. The model labeled as GAN is our benchmark model estimated with all characteristics and macroeconomic information. The portfolios are value-weighted.

Table IA.III: Explained Variation and Pricing Errors for Double-Sorted Portfolios based on Size and Value and Decile Sorted Portfolios based on Investment

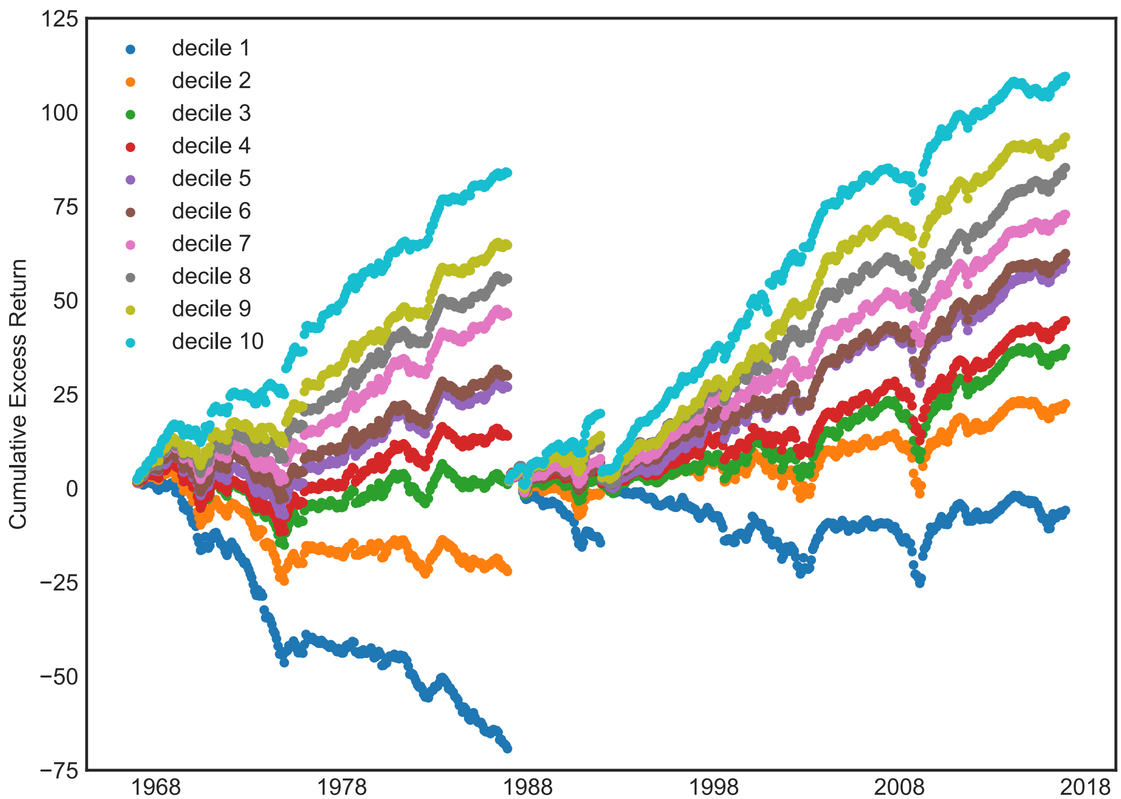
		UNC		GAN			GAN Full	UNC		GAN			GAN Full
		SV	SVI	SV-SV	SVI-SV	SVI-SVI	GAN	SV	SVI	SV-SV	SVI-SV	SVI-SVI	GAN
Investment		Explained Variation						Alpha					
1		0.66	0.69	0.69	0.65	0.67	0.61	-0.00	-0.02	0.01	-0.03	-0.02	0.01
2		0.75	0.75	0.76	0.70	0.71	0.71	0.00	-0.01	0.00	-0.02	-0.01	0.00
3		0.63	0.61	0.69	0.58	0.59	0.56	-0.03	-0.04	-0.01	-0.03	-0.02	-0.03
4		0.55	0.53	0.68	0.55	0.56	0.54	-0.06	-0.07	-0.04	-0.05	-0.05	-0.06
5		0.57	0.59	0.71	0.62	0.62	0.57	-0.05	-0.05	-0.02	-0.03	-0.03	-0.04
6		0.40	0.47	0.64	0.52	0.54	0.45	-0.05	-0.05	-0.02	-0.03	-0.02	-0.03
7		0.49	0.61	0.71	0.64	0.65	0.59	-0.06	-0.05	-0.02	-0.03	-0.01	-0.03
8		0.71	0.72	0.72	0.70	0.69	0.70	-0.07	-0.05	-0.02	-0.02	-0.01	-0.03
9		0.71	0.69	0.64	0.64	0.63	0.65	-0.05	-0.02	0.00	0.01	0.01	-0.00
10		0.73	0.69	0.63	0.61	0.62	0.62	-0.10	-0.07	-0.05	-0.03	-0.03	-0.04
LME	BEME	Explained Variation						Alpha					
1	1	0.14	0.13	-0.00	0.40	0.48	0.58	0.12	0.12	0.16	0.04	0.01	-0.04
1	2	0.09	0.28	0.32	0.57	0.62	0.69	0.15	0.11	0.09	0.02	-0.01	-0.03
1	3	0.23	0.48	0.64	0.69	0.71	0.73	0.22	0.16	0.08	0.08	0.06	0.02
1	4	0.40	0.65	0.68	0.74	0.74	0.73	0.20	0.13	0.03	0.06	0.04	0.02
1	5	0.54	0.70	0.53	0.70	0.69	0.74	0.17	0.10	-0.02	0.04	0.03	0.03
2	1	0.23	0.29	-0.03	0.56	0.67	0.64	0.08	0.07	0.13	0.01	-0.02	-0.01
2	2	0.22	0.47	0.41	0.76	0.81	0.78	0.14	0.09	0.10	0.02	-0.00	0.00
2	3	0.28	0.69	0.76	0.84	0.86	0.83	0.19	0.11	0.08	0.05	0.04	0.04
2	4	0.42	0.76	0.83	0.85	0.85	0.82	0.15	0.06	0.02	0.02	0.01	0.00
2	5	0.58	0.80	0.83	0.83	0.83	0.82	0.13	0.05	0.01	0.01	0.01	0.02
3	1	0.39	0.48	0.13	0.65	0.74	0.70	0.10	0.08	0.14	0.04	0.01	0.02
3	2	0.43	0.69	0.61	0.83	0.86	0.83	0.15	0.09	0.11	0.05	0.04	0.05
3	3	0.44	0.82	0.86	0.90	0.90	0.89	0.16	0.08	0.06	0.04	0.04	0.05
3	4	0.53	0.84	0.87	0.88	0.88	0.86	0.13	0.05	0.03	0.02	0.02	0.03
3	5	0.64	0.82	0.84	0.83	0.82	0.80	0.09	0.01	-0.00	-0.01	-0.01	0.02
4	1	0.76	0.73	0.49	0.75	0.80	0.79	0.01	0.02	0.07	0.01	-0.00	0.01
4	2	0.82	0.86	0.86	0.87	0.87	0.87	0.03	0.01	0.01	0.00	-0.00	0.00
4	3	0.75	0.88	0.88	0.86	0.85	0.85	0.07	0.01	-0.01	-0.00	0.00	0.01
4	4	0.75	0.88	0.89	0.87	0.86	0.85	0.06	0.00	-0.02	-0.01	0.00	0.01
4	5	0.76	0.81	0.83	0.80	0.80	0.79	0.03	-0.04	-0.04	-0.03	-0.02	-0.01
5	1	0.28	0.60	0.66	0.63	0.62	0.59	-0.11	-0.06	-0.02	-0.03	-0.03	-0.05
5	2	0.71	0.72	0.77	0.74	0.75	0.71	-0.06	-0.06	-0.04	-0.03	-0.02	-0.04
5	3	0.83	0.69	0.72	0.70	0.73	0.70	-0.02	-0.05	-0.05	-0.04	-0.02	-0.03
5	4	0.80	0.72	0.75	0.73	0.73	0.73	-0.04	-0.07	-0.06	-0.05	-0.03	-0.02
5	5	0.72	0.54	0.65	0.62	0.64	0.63	-0.05	-0.10	-0.07	-0.06	-0.04	-0.02
		Explained Variation						Cross-Sectional R^2					
All		0.48	0.60	0.57	0.70	0.72	0.72	0.60	0.82	0.86	0.96	0.98	0.97

This table shows the out-of-sample explained variation and pricing errors for the combined double sorted portfolios based on size (`LME`) and book-to-market ratio (`BEME`) and decile sorted portfolios based on investment (`Investment`). UNC (SV) and UNC (SVI) are unconditional models with respect to the test assets, that is, they use only size and value respectively size, value and investment for the SDF weights, but set g to a constant. The GAN models use a non-trivial g. GAN (SVI-SV) allows the SDF weight ω to depend on size, value and investment, but the test asset function g to depend only on size and investment. The model labeled as GAN is our benchmark model estimated with all characteristics and macroeconomic information. The portfolios are value-weighted.

IA.D. Predictive Portfolios

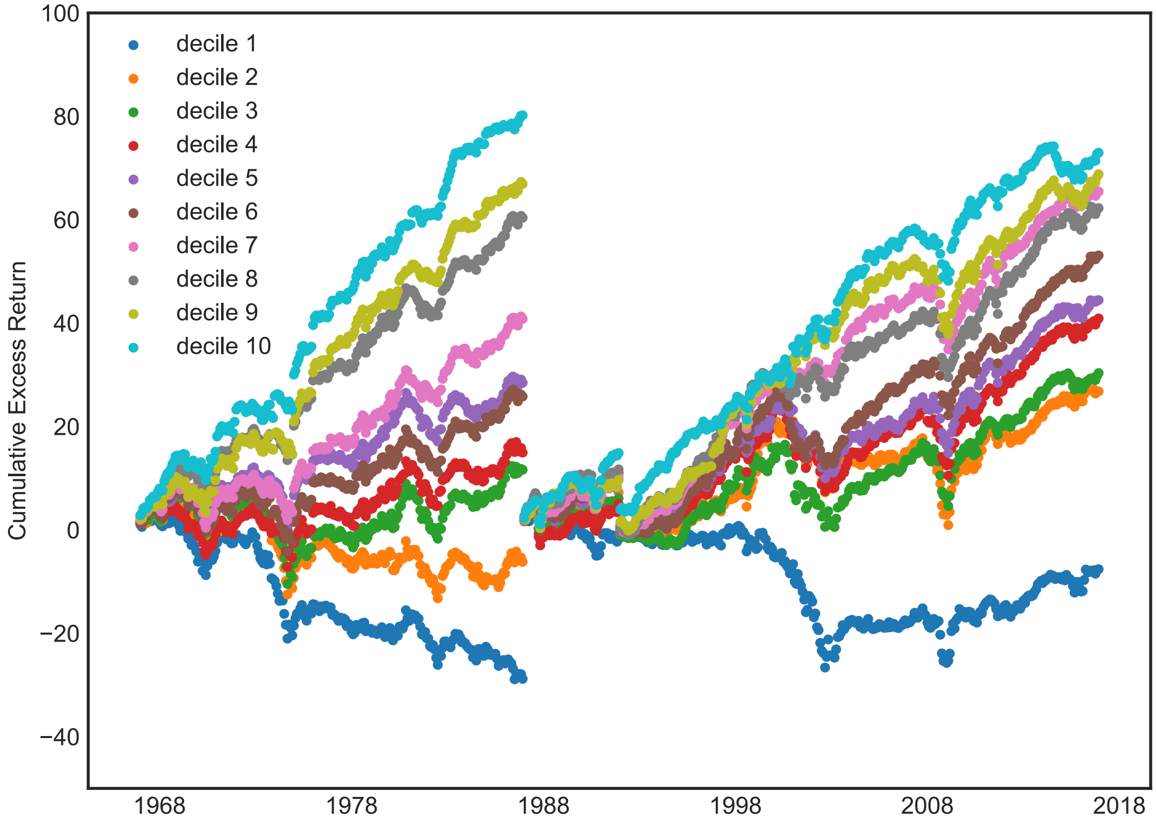
IA.D.1. Decile Sorted Portfolios for GAN

Figure IA.3: Cumulative Excess Return of Equally Weighted Decile Sorted Portfolios with GAN



This figure shows the cumulative excess return of decile sorted portfolios based on the risk loadings β. The first portfolio is based on the smallest decile of risk loadings, while the last decile portfolio is constructed with the largest loading decile. Within each decile the stocks are equally weighted.

Figure IA.4: Cumulative Excess Return of Value Weighted Decile β Portfolios with GAN



This figure shows the cumulative excess return of decile sorted portfolios based on the risk loadings β for GAN. The first portfolio is based on the smallest decile of risk loadings, while the last decile portfolio is constructed with the largest loading decile. Within each decile the stocks are value weighted.

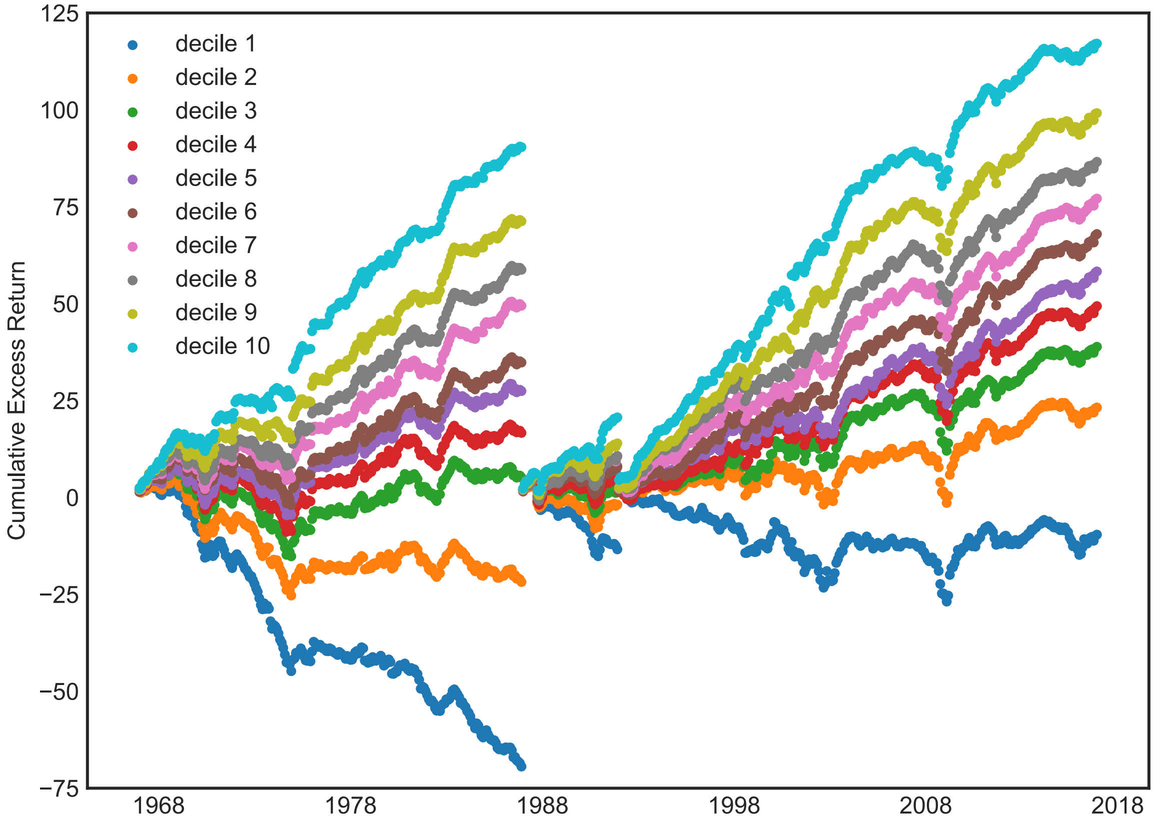
Table IA.IV: Time Series Pricing Errors for Value Weighted β-Sorted Portfolios

	Average Returns		Market-Rf				Fama-French 3				Fama-French 5			
	Whole	Test	Whole		Test		Whole		Test		Whole		Test	
Decile			α	t	α	t	α	t	α	t	α	t	α	t
1	-0.04	-0.02	-0.11	-6.10	-0.12	-3.87	-0.11	-5.99	-0.12	-3.90	-0.10	-5.14	-0.10	-3.28
2	0.03	0.05	-0.03	-2.87	-0.02	-1.19	-0.03	-2.28	-0.02	-0.91	-0.02	-2.07	-0.01	-0.72
3	0.05	0.06	-0.01	-1.43	-0.02	-1.01	-0.00	-0.48	-0.01	-0.34	-0.00	-0.12	-0.00	-0.05
4	0.06	0.07	-0.00	-0.50	0.00	0.13	0.00	0.49	0.01	0.92	0.00	0.27	0.01	0.89
5	0.08	0.08	0.02	2.04	0.01	0.52	0.02	2.63	0.01	1.08	0.02	2.07	0.01	0.43
6	0.09	0.10	0.02	2.62	0.02	1.69	0.03	2.86	0.03	2.11	0.02	2.32	0.03	1.67
7	0.12	0.12	0.05	5.23	0.05	3.27	0.05	4.87	0.05	3.24	0.04	3.52	0.03	2.10
8	0.14	0.11	0.08	6.37	0.04	2.71	0.07	5.52	0.04	2.32	0.05	4.10	0.02	1.11
9	0.18	0.15	0.11	6.56	0.07	3.24	0.08	5.47	0.05	2.52	0.06	4.32	0.03	1.39
10	0.29	0.24	0.20	7.20	0.13	3.38	0.15	6.72	0.10	2.88	0.16	6.88	0.11	3.01
10-1	0.33	0.26	0.31	10.00	0.25	5.61	0.26	9.68	0.22	5.23	0.25	9.19	0.22	4.90
GRS Asset Pricing Test			GRS	p	GRS	p	GRS	p	GRS	p	GRS	p	GRS	p
			11.15	0.00	3.94	0.00	10.29	0.00	3.76	0.00	8.80	0.00	2.87	0.00

This table shows the average returns, time series pricing errors and corresponding t-statistics for β-sorted decile portfolios based on GAN. The pricing errors are based on the CAPM and Fama-French 3 and 5 factors models. Returns are annualized. The GRS-test is under the null hypothesis of correctly pricing all decile portfolios and includes the p-values. We consider the full time period and the test period. Within each decile the stocks are value weighted.

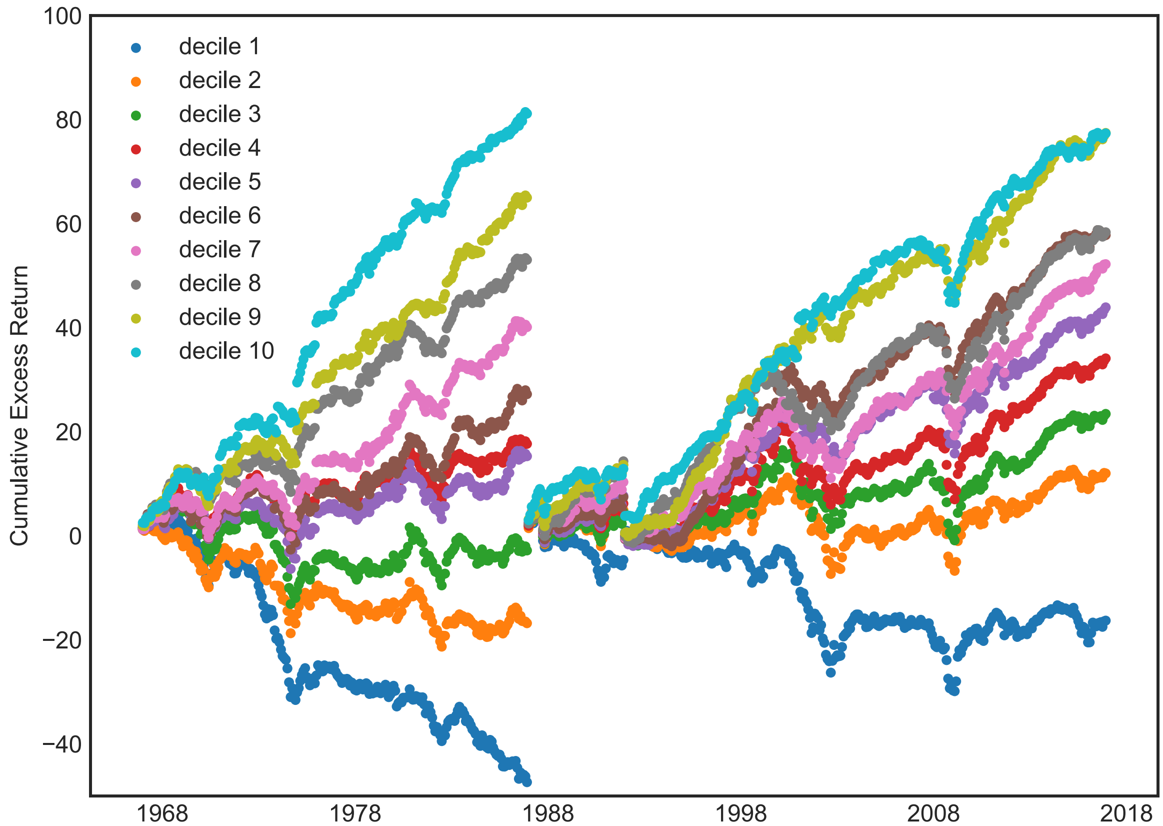
IA.D.2. Decile Sorted Portfolios for FFN

Figure IA.5: Cumulative Excess Return of Equally Weighted Decile β Portfolios with FFN



This figure shows the cumulative excess return of decile sorted portfolios based on the risk loadings β for FFN. The first portfolio is based on the smallest decile of risk loadings, while the last decile portfolio is constructed with the largest loading decile. Within each decile the stocks are equally weighted.

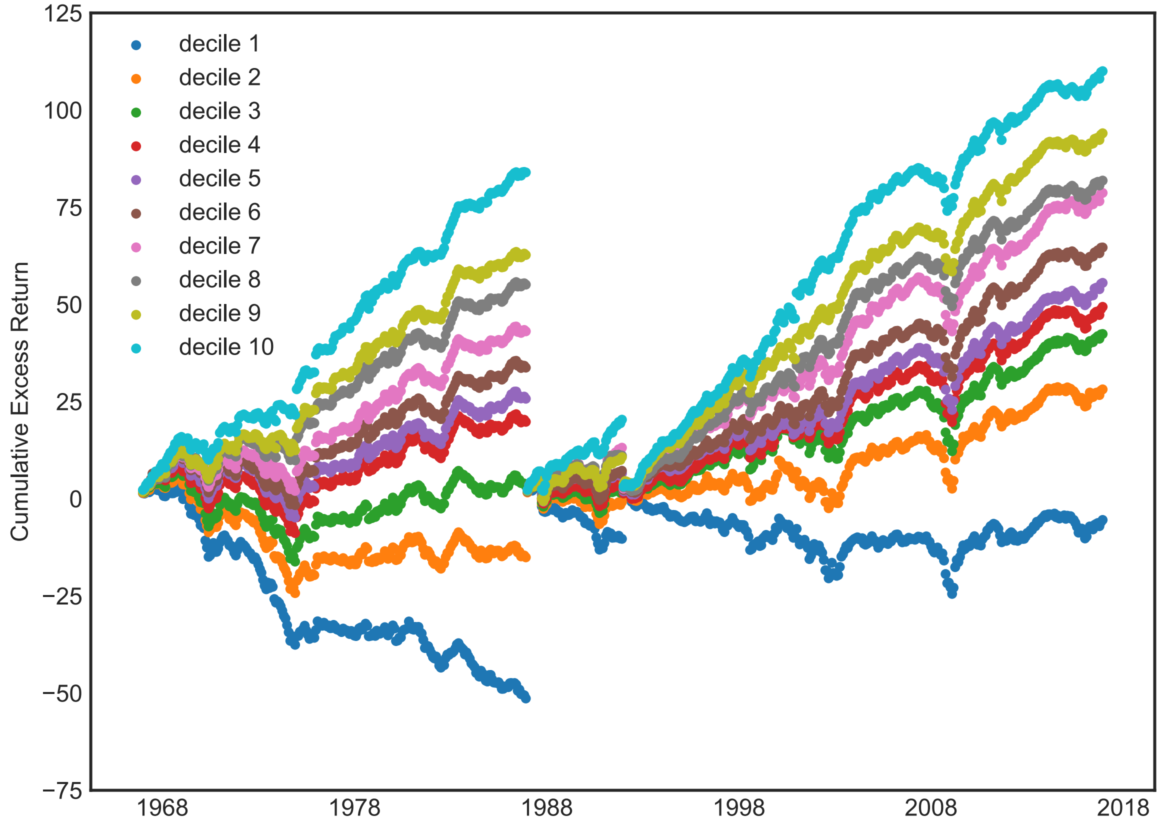
Figure IA.6: Cumulative Excess Return of Value Weighted Decile β Portfolios with FFN



This figure shows the cumulative excess return of decile sorted portfolios based on the risk loadings β for FFN. The first portfolio is based on the smallest decile of risk loadings, while the last decile portfolio is constructed with the largest loading decile. Within each decile the stocks are value weighted.

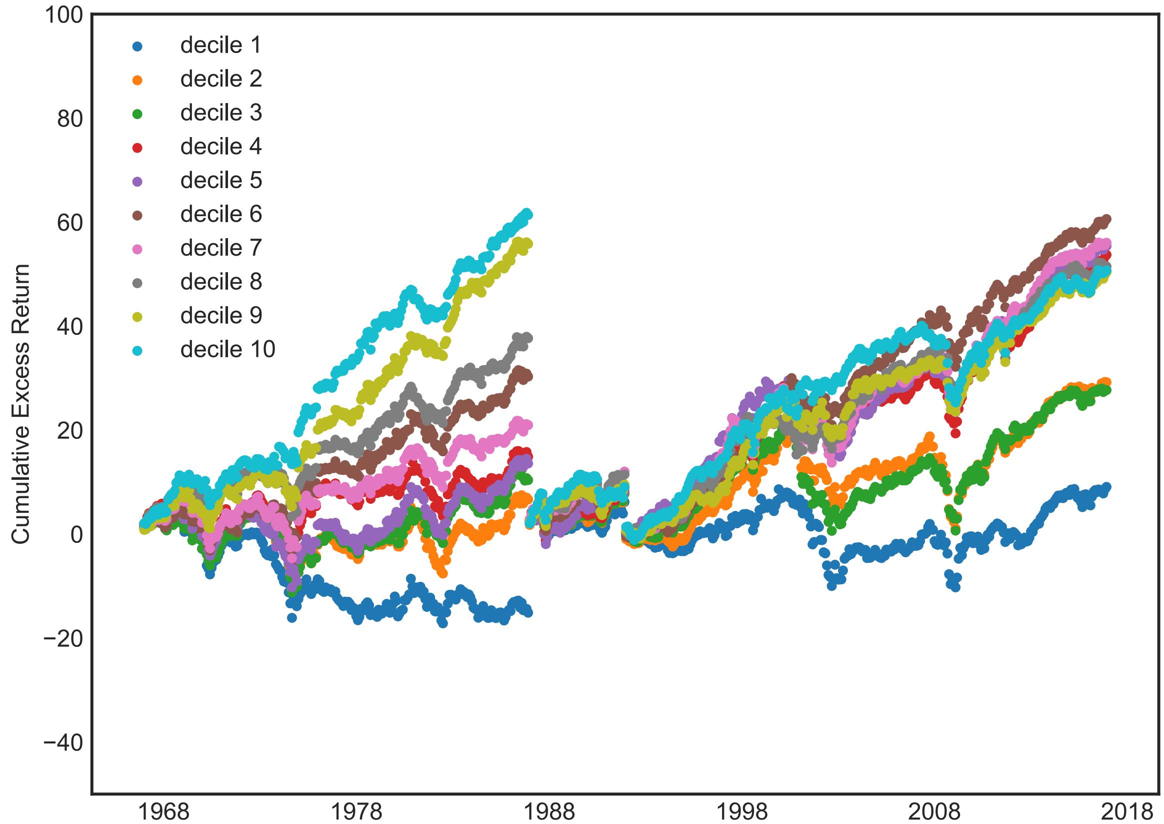
IA.D.3. Decile Sorted Portfolios for EN

Figure IA.7: Cumulative Excess Return of Equally Weighted Decile β Portfolios with EN



This figure shows the cumulative excess return of decile sorted portfolios based on the risk loadings β for EN. The first portfolio is based on the smallest decile of risk loadings, while the last decile portfolio is constructed with the largest loading decile. Within each decile the stocks are equally weighted.

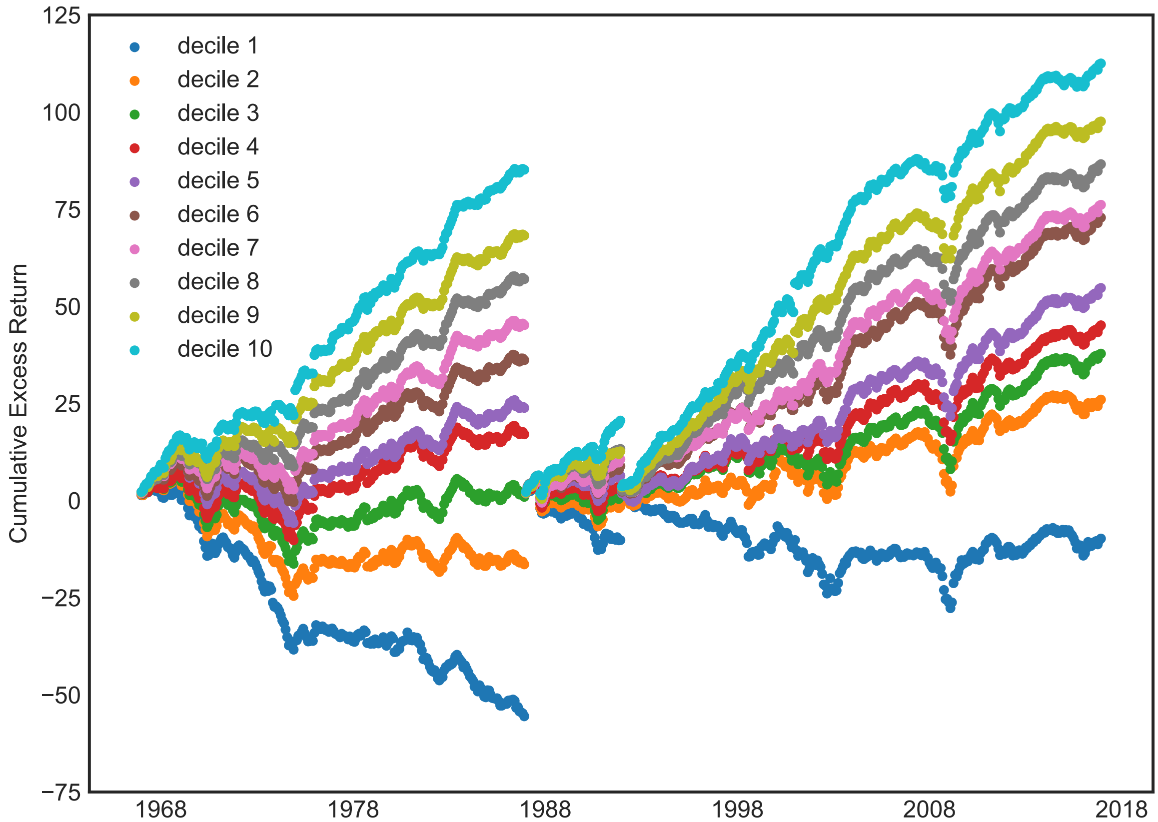
Figure IA.8: Cumulative Excess Return of Value Weighted Decile β Portfolios with EN



This figure shows the cumulative excess return of decile sorted portfolios based on the risk loadings β for EN. The first portfolio is based on the smallest decile of risk loadings, while the last decile portfolio is constructed with the largest loading decile. Within each decile the stocks are value weighted.

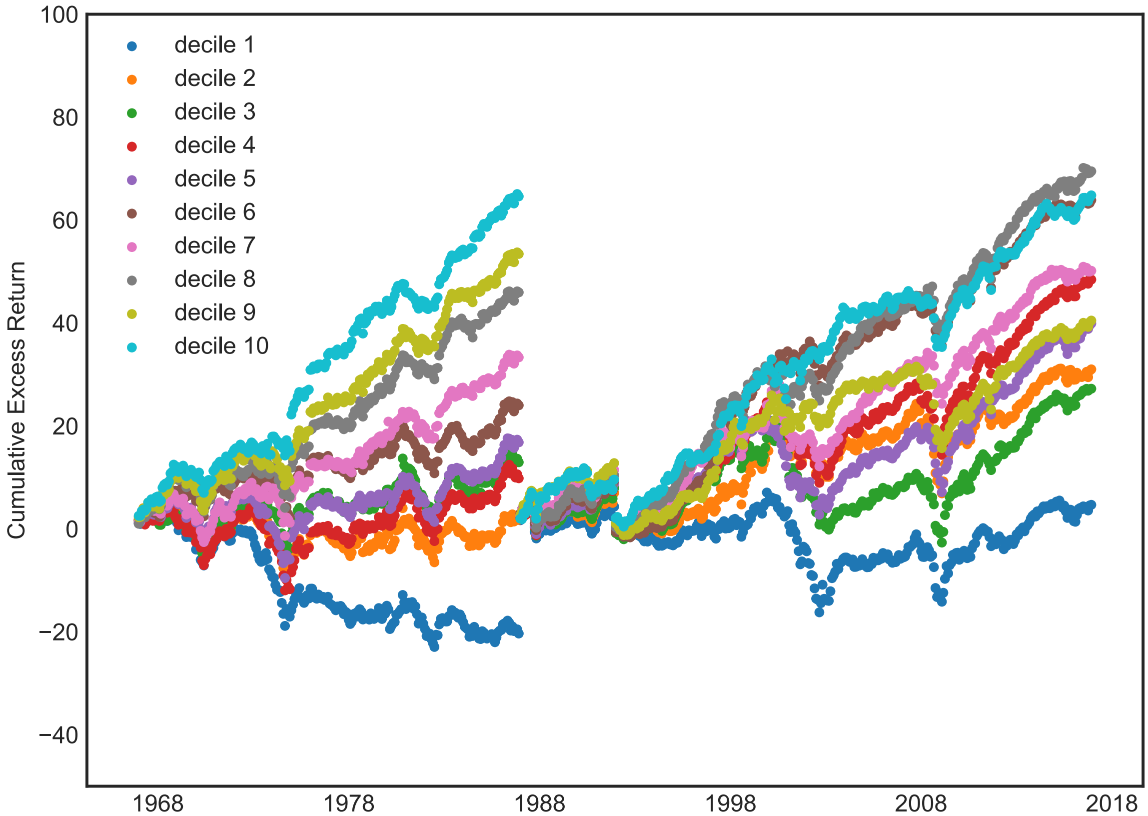
IA.D.4. Decile Sorted Portfolios for LS

Figure IA.9: Cumulative Excess Return of Equally Weighted Decile β Portfolios with LS



This figure shows the cumulative excess return of decile sorted portfolios based on the risk loadings β for LS. The first portfolio is based on the smallest decile of risk loadings, while the last decile portfolio is constructed with the largest loading decile. Within each decile the stocks are equally weighted.

Figure IA.10: Cumulative Excess Return of Value Weighted Decile β Portfolios with LS

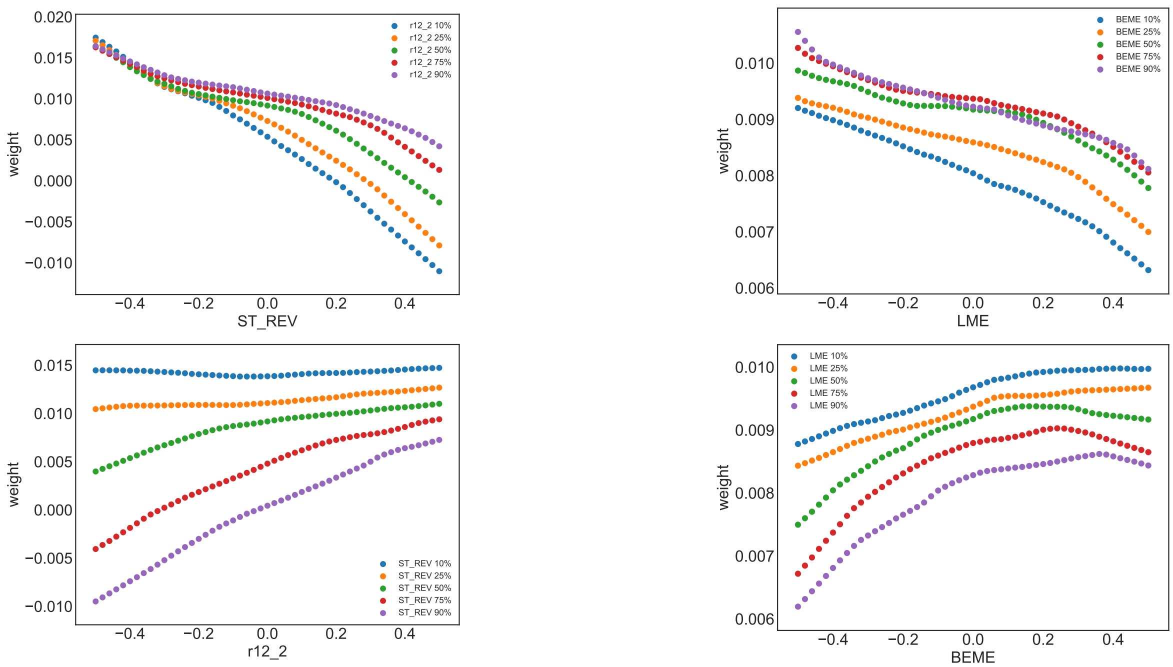


This figure shows the cumulative excess return of decile sorted portfolios based on the risk loadings β for LS. The first portfolio is based on the smallest decile of risk loadings, while the last decile portfolio is constructed with the largest loading decile. Within each decile the stocks are value weighted.

IA.E. SDF Structure for FFN, EN and LS

IA.E.1. SDF Structure for FFN

Figure IA.11: SDF weight ω as a Function of Characteristics for FFN

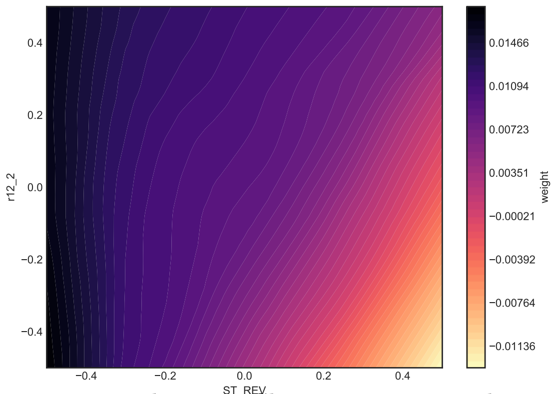


(a) Interaction between Short-Term Reversal (ST_REV) and Momentum (r12_2)

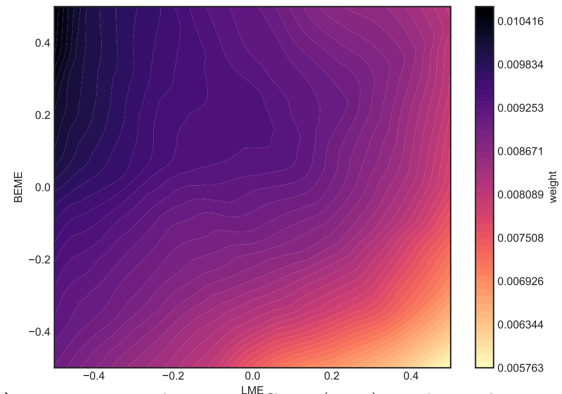
(b) Interaction between Size (LME) and Book to Market Ratio (BEME)

This figures show the SDF weight ω as function of short-term reversal, momentum, size and book-to-market ratio for different quantiles of the second variable while keeping the remaining variables at their mean level.

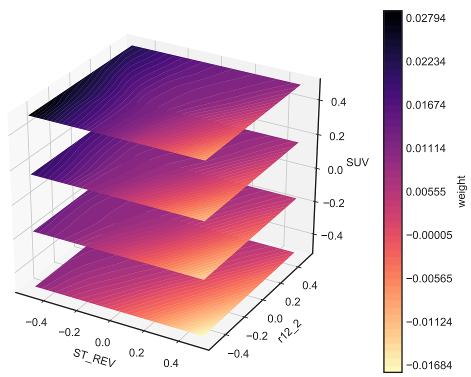
Figure IA.12: SDF weight ω as a Function of Characteristics for FFN



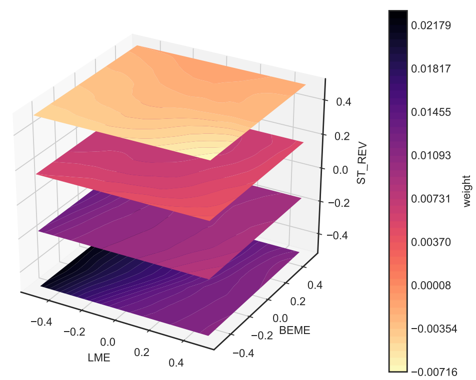
(a) Interaction between Short-Term Reversal (`ST_REV`) and Momentum (`r12_2`)



(b) Interaction between Size (`LME`) and Book to Market Ratio (`BEME`)



(c) Interaction between Short-Term Reversal (`ST_REV`), Momentum (`r12_2`) and Standard Unexplained Volume (`SUV`)

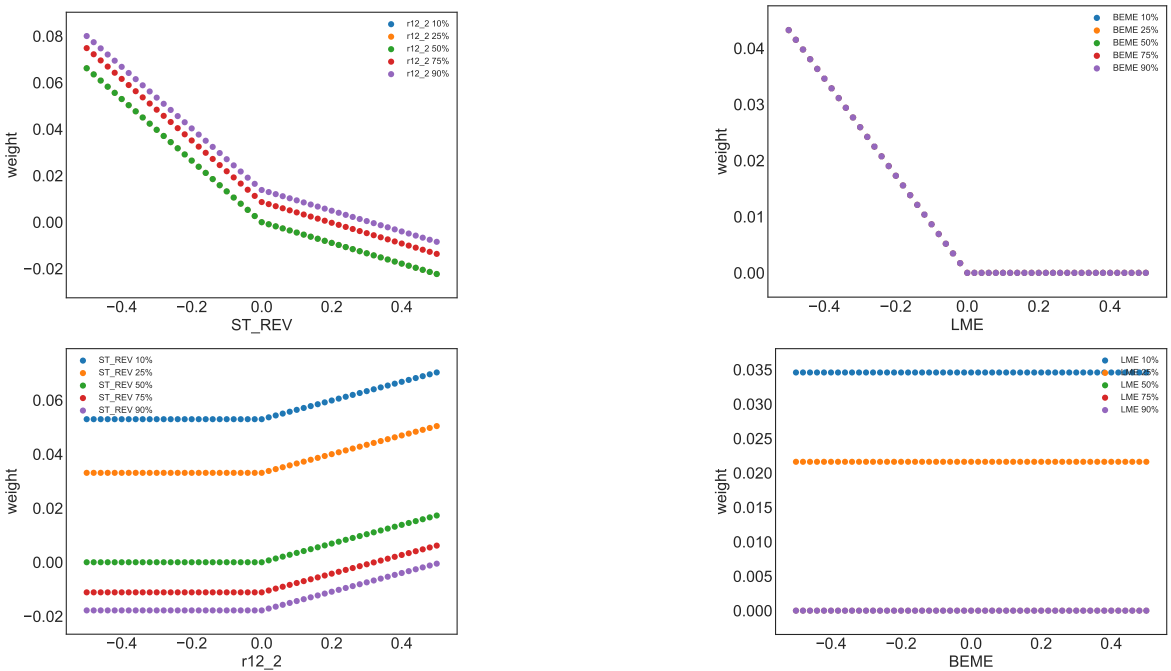


(d) Interaction between Size (`LME`), Book to Market Ratio (`BEME`) and Short-Term Reversal (`ST_REV`)

These figures show the SDF weight ω as two- and three-dimensional functions of characteristics keeping the remaining variables at their mean level.

IA.E.2. SDF Structure for EN

Figure IA.13: SDF weight ω as a Function of Characteristics for EN

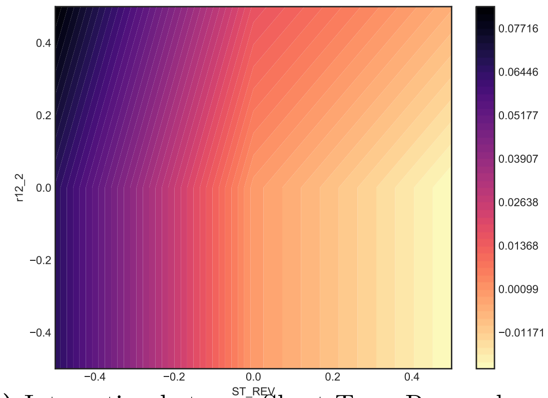


(a) Interaction between Short-Term Reversal (`ST_REV`) and Momentum (`r12_2`)

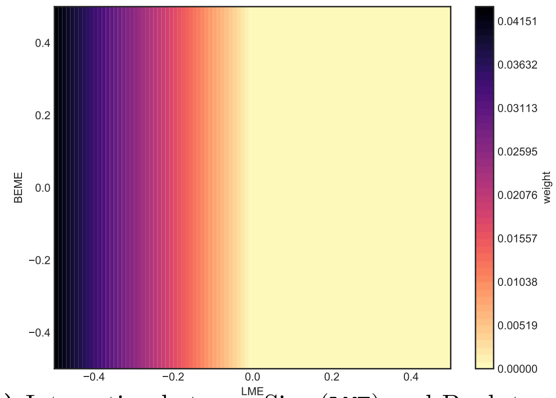
(b) Interaction between Size (`LME`) and Book to Market Ratio (`BEME`)

This figures show the SDF weight ω as function of short-term reversal, momentum, size and book-to-market ratio for different quantiles of the second variable while keeping the remaining variables at their mean level.

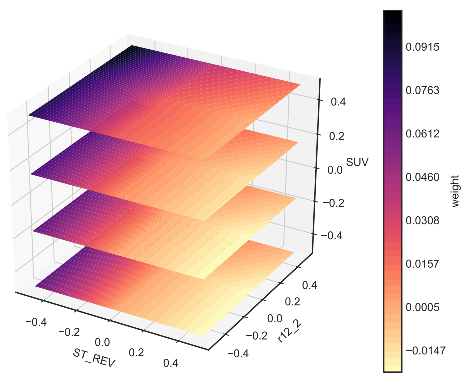
Figure IA.14: SDF weight ω as a Function of Characteristics for EN



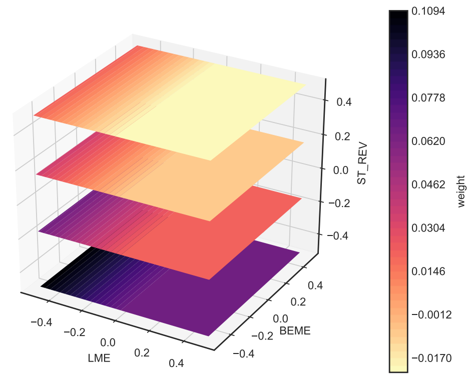
(a) Interaction between Short-Term Reversal (`ST_REV`) and Momentum (`r12_2`)



(b) Interaction between Size (`LME`) and Book to Market Ratio (`BEME`)



(c) Interaction between Short-Term Reversal (`ST_REV`), Momentum (`r12_2`) and Standard Unexplained Volume (`SUV`)

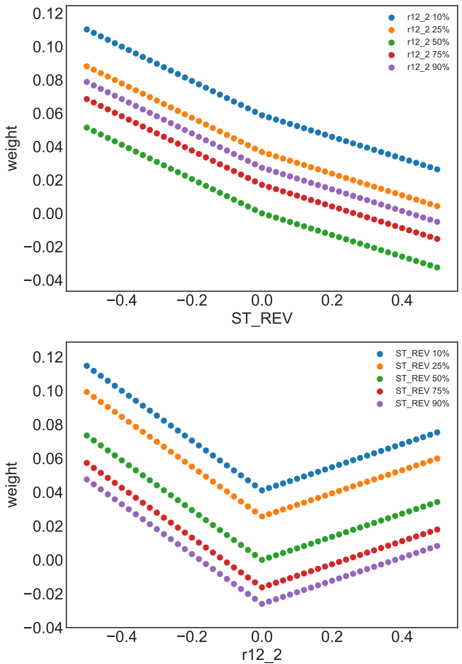


(d) Interaction between Size (`LME`), Book to Market Ratio (`BEME`) and Short-Term Reversal (`ST_REV`)

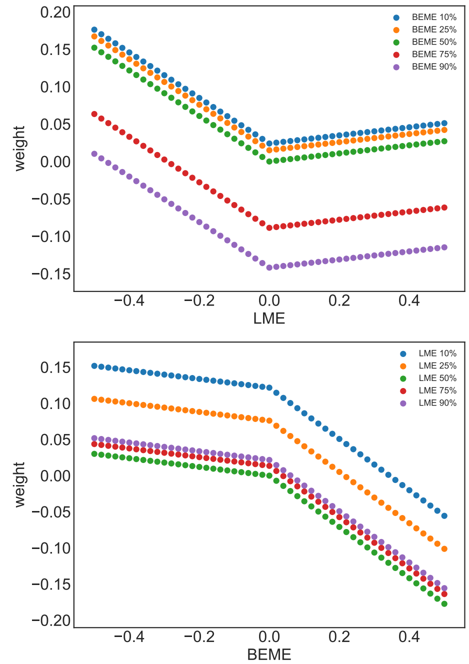
These figures show the SDF weight ω as two- and three-dimensional functions of characteristics keeping the remaining variables at their mean level.

IA.E.3. SDF Structure for LS

Figure IA.15: SDF weight ω as a Function of Characteristics for LS



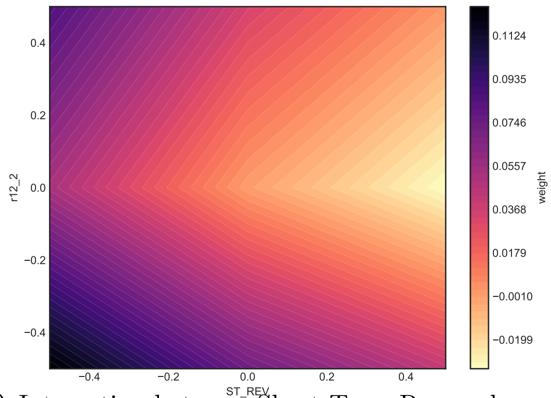
(a) Interaction between Short-Term Reversal (`ST_REV`) and Momentum (`r12_2`)



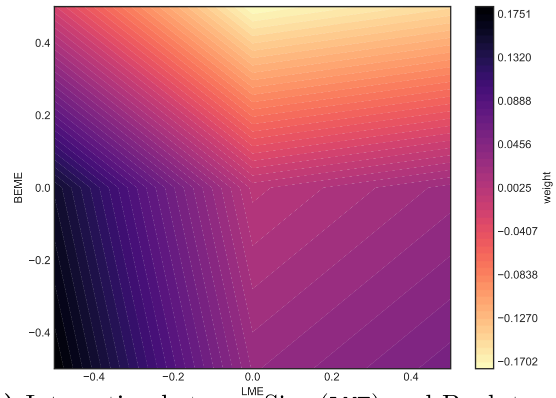
(b) Interaction between Size (`LME`) and Book to Market Ratio (`BEME`)

This figures show the SDF weight ω as function of short-term reversal, momentum, size and book-to-market ratio for different quantiles of the second variable while keeping the remaining variables at their mean level.

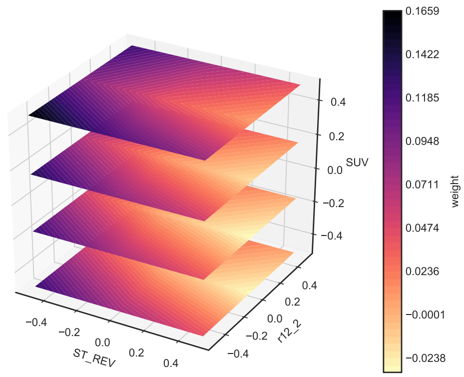
Figure IA.16: SDF weight ω as a Function of Characteristics for LS



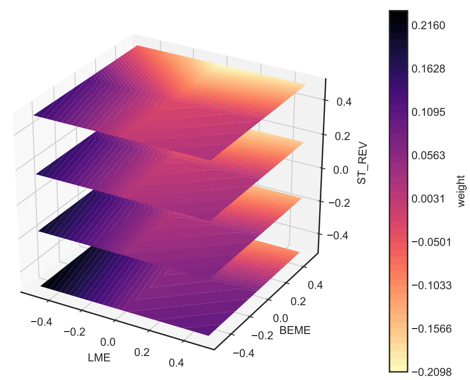
(a) Interaction between Short-Term Reversal (`ST_REV`) and Momentum (`r12_2`)



(b) Interaction between Size (`LME`) and Book to Market Ratio (`BEME`)



(c) Interaction between Short-Term Reversal (`ST_REV`), Momentum (`r12_2`) and Standard Unexplained Volume (`SUV`)



(d) Interaction between Size (`LME`), Book to Market Ratio (`BEME`) and Short-Term Reversal (`ST_REV`)

These figures show the SDF weight ω as two- and three-dimensional functions of characteristics keeping the remaining variables at their mean level.

IA.F. Machine-Learning Investment

Table IA.V: Sharpe Ratio of Long-Short Portfolios with FFN

Quantile	SR (Train)	SR (Valid)	SR (Test)
(i) Equally Weighted			
1%	1.24	0.65	0.66
5%	1.36	1.10	0.71
10%	1.30	1.31	0.67
25%	1.19	1.20	0.57
50%	1.09	1.26	0.52
(ii) Value Weighted			
1%	0.98	0.35	0.39
5%	0.89	0.71	0.42
10%	0.70	0.45	0.32
25%	0.55	0.28	0.17
50%	0.43	0.20	0.15

This table shows monthly Sharpe Ratios of long-short portfolios based on the extreme deciles of returns predicted by FFN. The model is a 3-layer feedforward network, and the hidden layers have 32, 16 and 8 neurons. The predictors are 46 firm-specific characteristics. The stocks are sorted into quantiles (1%, 5%, 10%, 25% and 50%) based on forecasts. A zero-net-investment portfolio is constructed by buying the highest expected return stocks and selling the lowest with equal weights or value weighted by market capitalization.

Table IA.VI: SDF Risk Measures for Large Market Cap Stocks

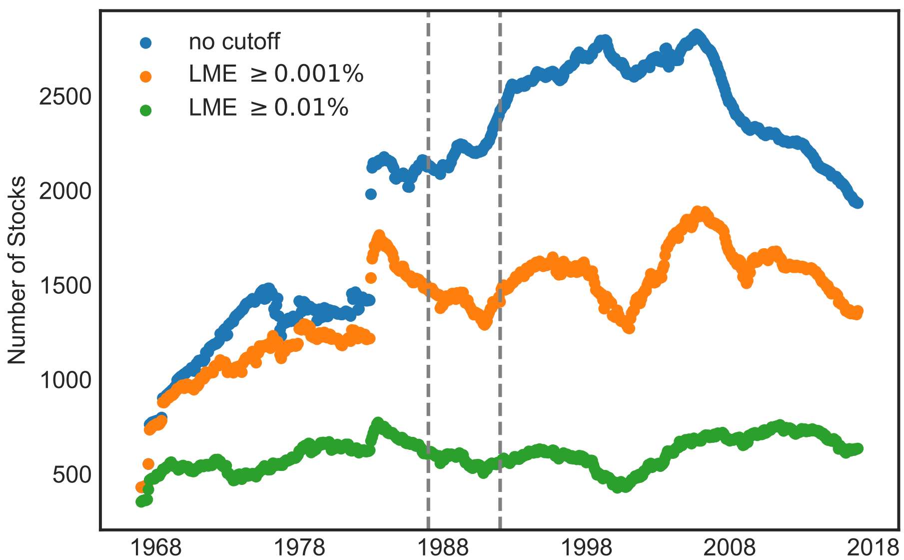
	SR			Max Loss			Max Drawdown		
Model	Train	Valid	Test	Train	Valid	Test	Train	Valid	Test
Size $\geq$ 0.001% of total market cap									
LS	1.44	0.31	0.13	-3.07	-2.19	-4.59	1	3	7
EN	0.93	0.56	0.15	-3.00	-2.45	-4.82	2	3	5
FFN	0.42	0.20	0.30	-3.89	-4.66	-4.33	6	4	5
GAN	2.32	1.09	0.41	-1.17	-1.14	-4.84	1	1	5
Size $\geq$ 0.01% of total market cap									
LS	0.32	-0.11	-0.06	-3.11	-1.82	-3.67	4	5	7
EN	0.37	0.26	0.23	-4.44	-2.67	-4.66	4	3	7
FFN	0.32	0.17	0.24	-3.30	-4.53	-5.08	7	5	5
GAN	0.97	0.54	0.26	-6.91	-1.36	-5.01	2	2	7

The table shows the monthly Sharpe Ratio, maximum 1-month loss and maximum drawdown of the SDF portfolios for the GAN, FFN, EN and LS models. The models are estimated on all stocks but evaluated on stocks with market capitalization larger than 0.01% or 0.001% of the total market capitalization.

IA.G. Robustness Results

IA.G.1. Market Capitalization

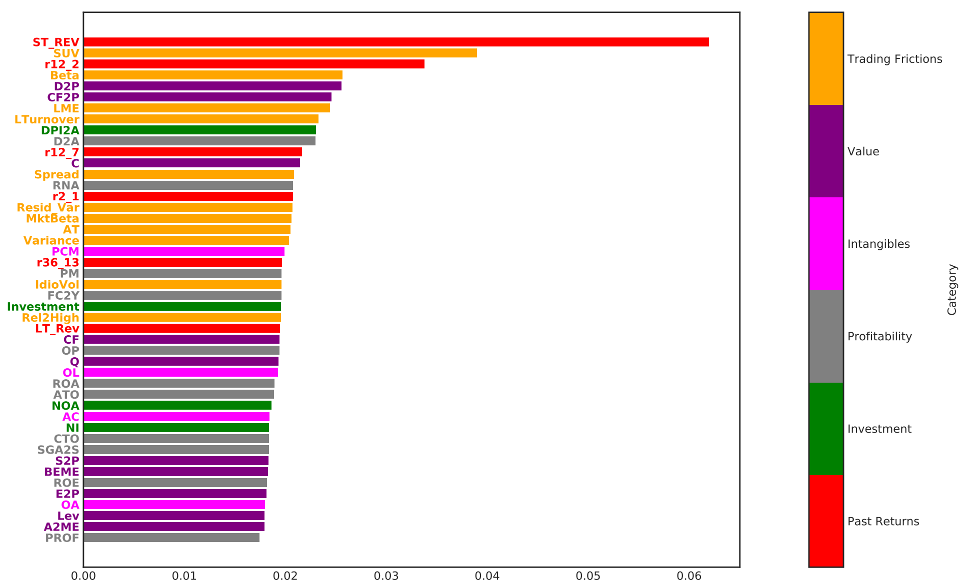
Figure IA.17: Number of Stocks per Month



This plots shows the number of stocks per month in the total sample and for stocks with market capitalization larger than 0.01% or 0.001% of the total market capitalization.

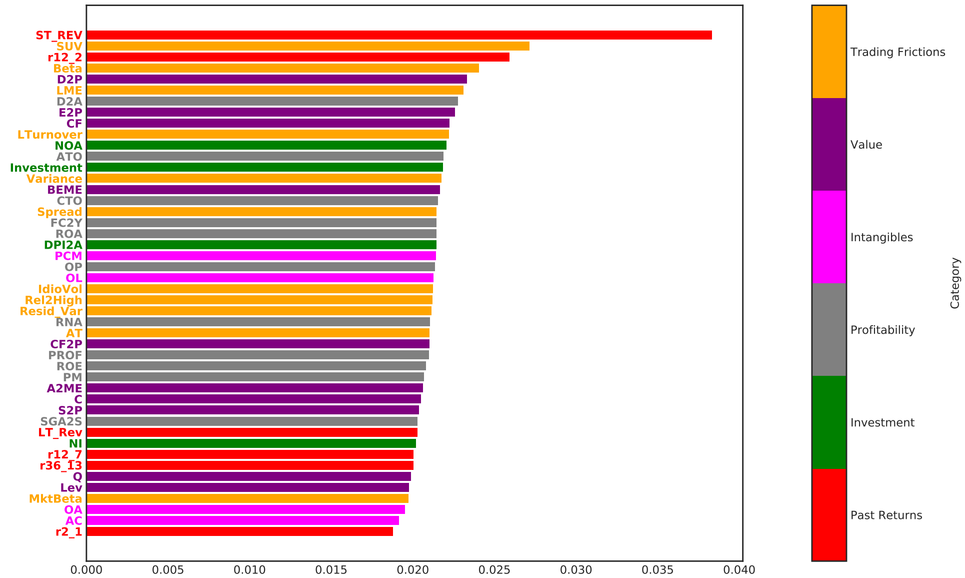
IA.G.2. Characteristic Importance for Alternative GAN Models

Figure IA.18: Characteristic Importance of SDF for GAN 1



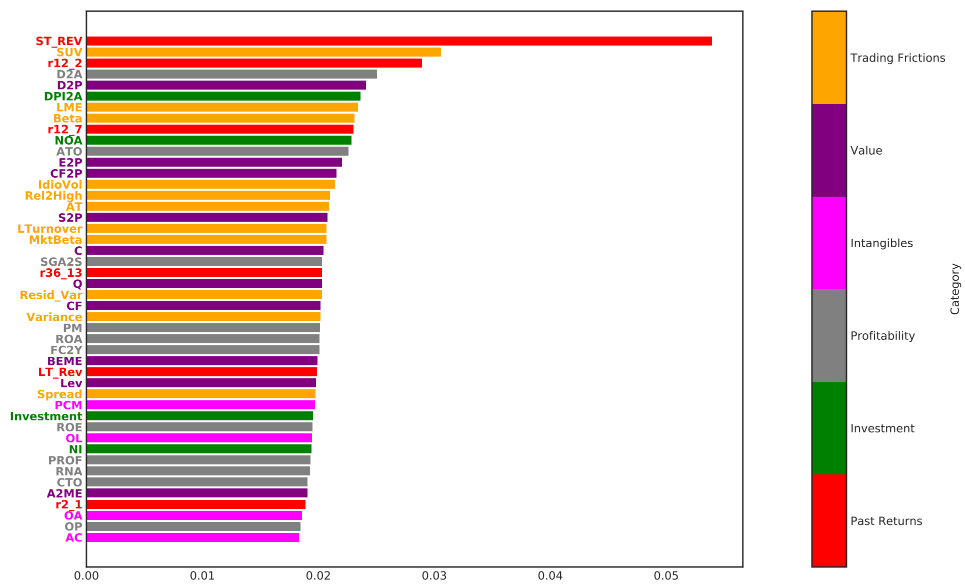
The figure shows the GAN 1 SDF variable importance ranking of the 46 firm-specific characteristics in terms of average absolute gradient (VI) on the test data. The values are normalized to sum up to one.

Figure IA.19: Characteristic Importance of SDF for GAN 2



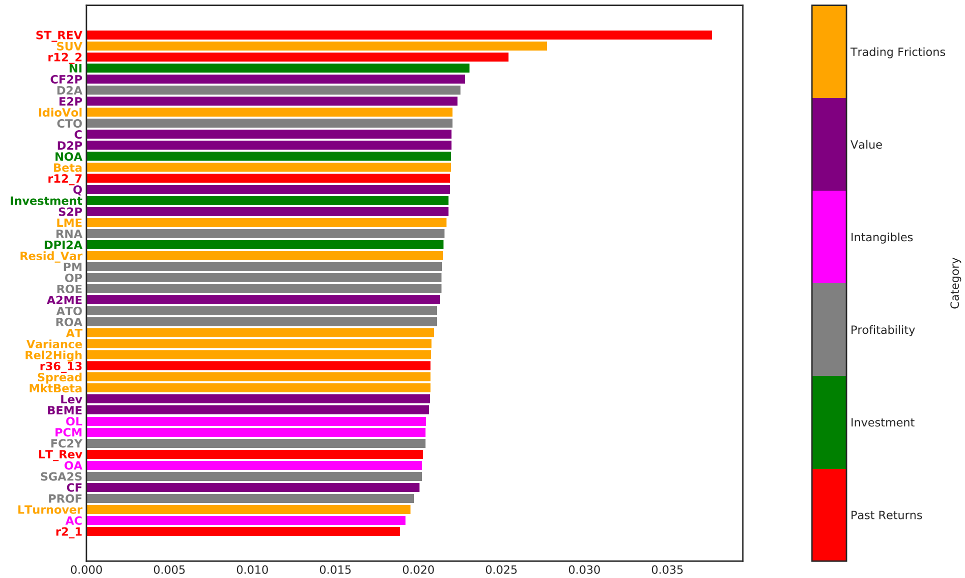
The figure shows the GAN 2 SDF variable importance ranking of the 46 firm-specific characteristics in terms of average absolute gradient (VI) on the test data. The values are normalized to sum up to one.

Figure IA.20: Characteristic Importance of SDF for GAN 3



The figure shows the GAN 3 SDF variable importance ranking of the 46 firm-specific characteristics in terms of average absolute gradient (VI) on the test data. The values are normalized to sum up to one.

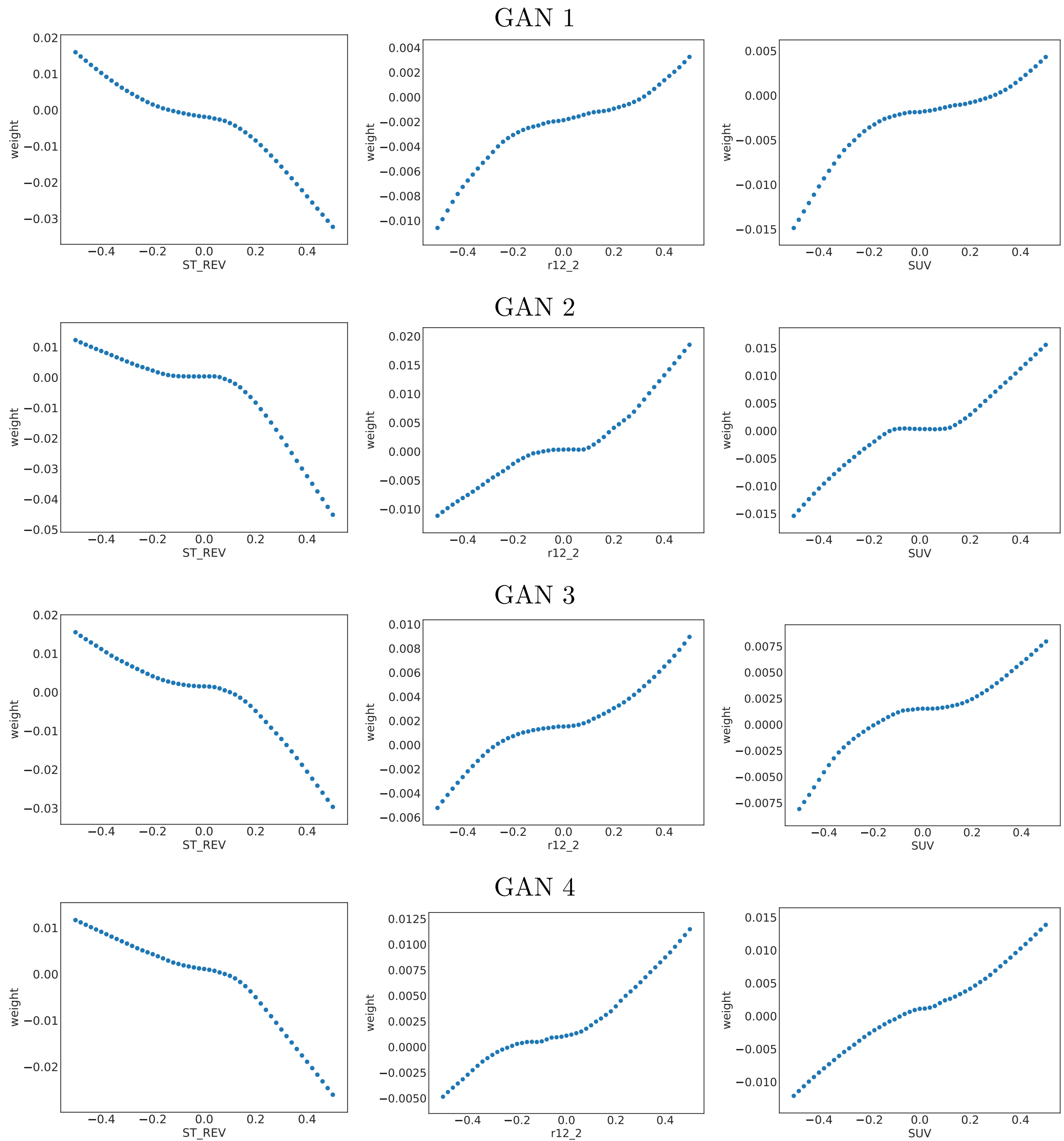
Figure IA.21: Characteristic Importance of SDF for GAN 4



The figure shows the GAN 4 SDF variable importance ranking of the 46 firm-specific characteristics in terms of average absolute gradient (VI) on the test data. The values are normalized to sum up to one.

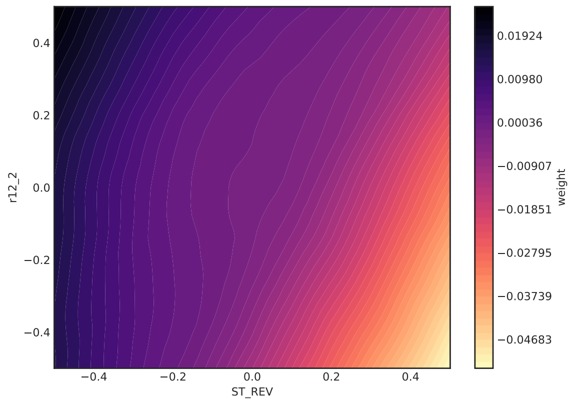
IA.G.3. SDF Structure for Alternative GAN Models

Figure IA.22: SDF weight ω as a Function of Characteristics for GAN 1-4

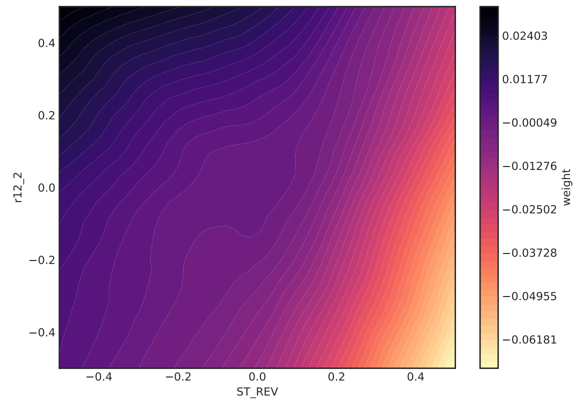


This figure shows the SDF weight ω as a one-dimensional function of characteristics keeping the other covariates at their mean level for alternative GAN models. The covariates are Short-Term Reversal (`ST_REV`), Momentum (`r12_2`) and Standard Unexplained Volume (`SUV`). The re-estimation of the GAN model is independent of the benchmark GAN model. GAN 1 has 4 layers, 32 instruments and 4 hidden states. GAN 2 has 2 layers, 8 instruments and 4 hidden states and the hence the same architecture as our benchmark model. GAN 3 has 4 layers, 16 instruments and 4 hidden states, while GAN 4 has 3 layers, 16 instruments and 4 hidden states.

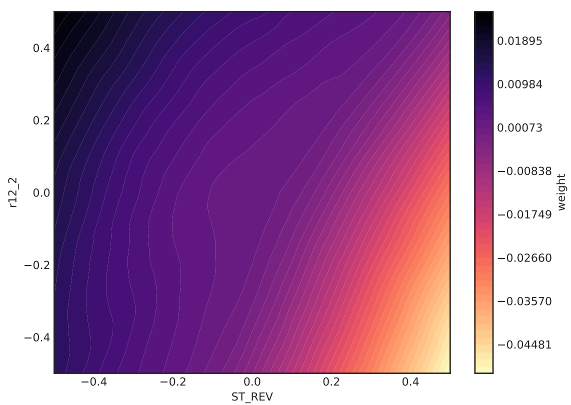
Figure IA.23: SDF weight ω as a Function of Characteristics for GAN



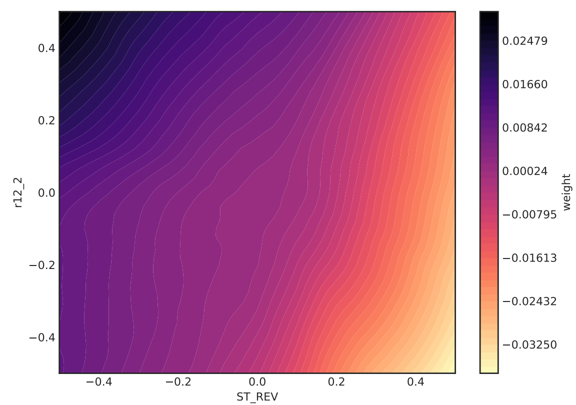
(a) Interaction between Short-Term Reversal (ST_REV) and Momentum (r12_2) for GAN 1



(b) Interaction between Short-Term Reversal (ST_REV) and Momentum (r12_2) for GAN 2



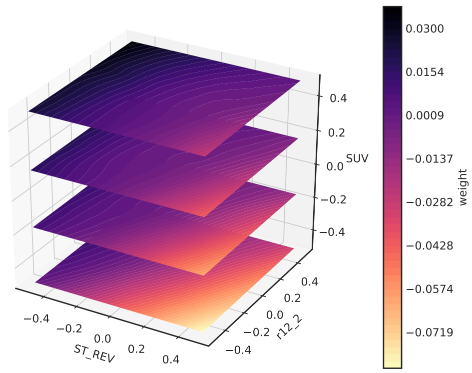
(c) Interaction between Short-Term Reversal (ST_REV) and Momentum (r12_2) for GAN 3



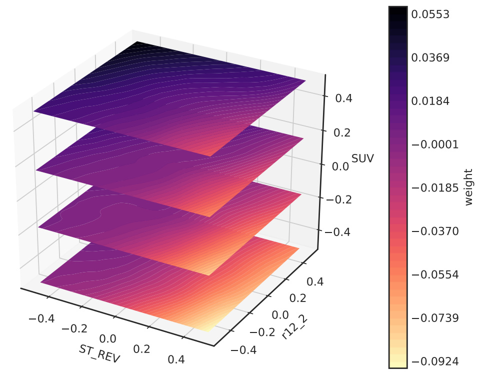
(d) Interaction between Short-Term Reversal (ST_REV) and Momentum (r12_2) for GAN 4

These figures show the SDF weight ω for alternative GAN models as two-dimensional function of characteristics keeping the remaining variables at their mean level. The re-estimation of the GAN model is independent of the benchmark GAN model. GAN 1 has 4 layers, 32 instruments and 4 hidden states. GAN 2 has 2 layers, 8 instruments and 4 hidden states and the hence the same architecture as our benchmark model. GAN 3 has 4 layers, 16 instruments and 4 hidden states, while GAN 4 has 3 layers, 16 instruments and 4 hidden states.

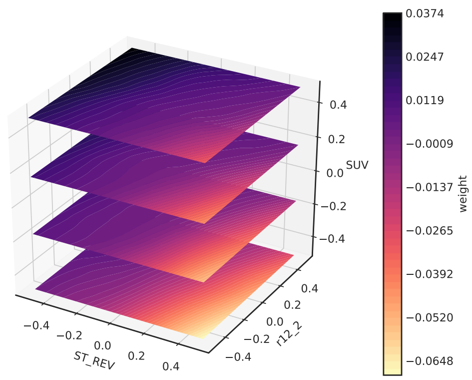
Figure IA.24: SDF weight ω as a Function of Characteristics for GAN



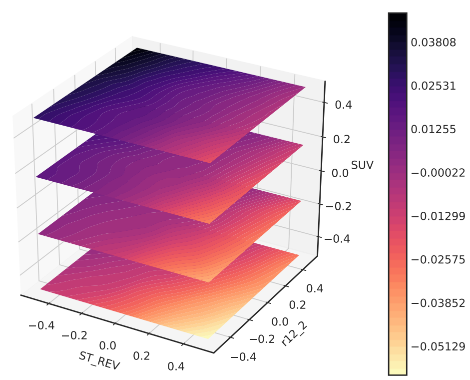
(a) Interaction between Short-Term Reversal (ST_REV), Momentum (r12_2) and Standard Unexplained Volume (SUV) for GAN 1



(b) IInteraction between Short-Term Reversal (ST_REV), Momentum (r12_2) and Standard Unexplained Volume (SUV) for GAN 2



(c) Interaction between Short-Term Reversal (ST_REV), Momentum (r12_2) and Standard Unexplained Volume (SUV) for GAN 3



(d) Interaction between Short-Term Reversal (ST_REV), Momentum (r12_2) and Standard Unexplained Volume (SUV) for GAN 4

These figures show the SDF weight ω for alternative GAN models as three-dimensional function of characteristics keeping the remaining variables at their mean level. The re-estimation of the GAN model is independent of the benchmark GAN model. GAN 1 has 4 layers, 32 instruments and 4 hidden states. GAN 2 has 2 layers, 8 instruments and 4 hidden states and the hence the same architecture as our benchmark model. GAN 3 has 4 layers, 16 instruments and 4 hidden states, while GAN 4 has 3 layers, 16 instruments and 4 hidden states.

IA.H. SDF of Multi-Factor Models

Table IA.VII: IPCA GAN

	3	4	5	6	7	8	9	10
SR Train	1.60	1.65	1.82	1.80	1.86	1.82	1.86	1.87
SR Valid	1.00	1.20	1.28	1.26	1.53	1.44	1.22	1.34
SR Test	0.61	0.71	0.77	0.70	0.79	0.82	0.72	0.81
EV Train	0.13	0.12	0.11	0.13	0.13	0.15	0.12	0.14
EV Valid	0.05	0.05	0.04	0.05	0.05	0.06	0.04	0.06
EV Test	0.05	0.04	0.04	0.05	0.05	0.05	0.04	0.05
XS-R^2 Train	0.03	0.02	0.01	0.02	0.01	0.01	0.01	0.02
XS-R^2 Valid	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
XS-R^2 Test	0.20	0.19	0.17	0.20	0.18	0.20	0.17	0.21

This table shows the asset pricing results for different SDFs based on IPCA. We consider $K = 3$ to 10 IPCA factors. $(\omega^{\text{I-GAN}}, \beta^{\text{I-GAN}})$ uses the GAN framework to estimate the SDF weights of IPCA factors and the SDF loading. $(\omega^{\text{I-SR}}, \beta^{\text{I-FFN}})$ is the unconditional mean-variance efficient combination of IPCA factors with flexible SDF weights. $(\omega^{\text{I-SR}}, \beta^{\text{I-SR}})$ restricts those weights to be linear. $(\omega^{\text{I-XS}}, \beta^{\text{I-EV}})$ combines the IPCA factors to maximize EV while $(\omega^{\text{I-XS}}, \beta^{\text{I-XS}})$ maximizes XS-R^2. The multi-factor representation obtains the residuals with a cross-sectional regression on the multiple loadings. The SDF weights and loadings are estimated on the training data and tuning parameters are chosen optimally on the validation data set.

Table IA.VIII: IPCA Max SR FFN Beta

	3	4	5	6	7	8	9	10
SR Train	1.59	1.67	1.78	1.82	1.85	1.88	1.88	1.95
SR Valid	1.12	1.27	1.37	1.42	1.42	1.42	1.45	1.50
SR Test	0.69	0.79	0.82	0.84	0.83	0.86	0.86	0.94
EV Train	0.10	0.09	0.08	0.10	0.10	0.10	0.16	0.10
EV Valid	0.05	0.04	0.03	0.04	0.04	0.04	0.07	0.04
EV Test	0.04	0.03	0.03	0.04	0.04	0.04	0.06	0.03
XS-R^2 Train	0.12	0.15	0.13	0.13	0.14	0.14	0.13	0.14
XS-R^2 Valid	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.01
XS-R^2 Test	0.14	0.13	0.11	0.14	0.14	0.15	0.19	0.14

This table shows the asset pricing results for different SDFs based on IPCA. We consider $K = 3$ to 10 IPCA factors. $(\omega^{\text{I-GAN}}, \beta^{\text{I-GAN}})$ uses the GAN framework to estimate the SDF weights of IPCA factors and the SDF loading. $(\omega^{\text{I-SR}}, \beta^{\text{I-FFN}})$ is the unconditional mean-variance efficient combination of IPCA factors with flexible SDF weights. $(\omega^{\text{I-SR}}, \beta^{\text{I-SR}})$ restricts those weights to be linear. $(\omega^{\text{I-XS}}, \beta^{\text{I-EV}})$ combines the IPCA factors to maximize EV while $(\omega^{\text{I-XS}}, \beta^{\text{I-XS}})$ maximizes XS-R^2. The multi-factor representation obtains the residuals with a cross-sectional regression on the multiple loadings. The SDF weights and loadings are estimated on the training data and tuning parameters are chosen optimally on the validation data set.

Table IA.IX: IPCA Max SR

	3	4	5	6	7	8	9	10
SR Train	1.59	1.67	1.78	1.82	1.85	1.88	1.88	1.95
SR Valid	1.12	1.27	1.37	1.42	1.42	1.42	1.45	1.50
SR Test	0.69	0.79	0.82	0.84	0.83	0.86	0.86	0.94
EV Train	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
EV Valid	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
EV Test	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
XS-R^2 Train	-0.05	-0.04	-0.04	-0.03	-0.03	-0.03	-0.03	-0.04
XS-R^2 Valid	0.03	0.02	0.02	0.04	0.04	0.04	0.03	0.03
XS-R^2 Test	-0.05	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04

This table shows the asset pricing results for different SDFs based on IPCA. We consider $K = 3$ to 10 IPCA factors. $(\omega^{\text{I-GAN}}, \beta^{\text{I-GAN}})$ uses the GAN framework to estimate the SDF weights of IPCA factors and the SDF loading. $(\omega^{\text{I-SR}}, \beta^{\text{I-FFN}})$ is the unconditional mean-variance efficient combination of IPCA factors with flexible SDF weights. $(\omega^{\text{I-SR}}, \beta^{\text{I-SR}})$ restricts those weights to be linear. $(\omega^{\text{I-XS}}, \beta^{\text{I-EV}})$ combines the IPCA factors to maximize EV while $(\omega^{\text{I-XS}}, \beta^{\text{I-XS}})$ maximizes XS-R^2. The multi-factor representation obtains the residuals with a cross-sectional regression on the multiple loadings. The SDF weights and loadings are estimated on the training data and tuning parameters are chosen optimally on the validation data set.

Table IA.X: IPCA Max EV

	3	4	5	6	7	8	9	10
SR Train	0.03	0.05	0.14	0.19	0.10	0.11	0.09	0.10
SR Valid	-0.02	-0.01	0.07	0.12	0.05	0.06	0.02	0.07
SR Test	0.11	0.11	0.15	0.17	0.15	0.15	0.14	0.16
EV Train	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
EV Valid	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
EV Test	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
XS-R^2 Train	0.05	0.04	0.03	0.01	0.03	0.03	0.03	0.03
XS-R^2 Valid	0.00	0.00	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01
XS-R^2 Test	-0.02	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03

This table shows the asset pricing results for different SDFs based on IPCA. We consider $K = 3$ to 10 IPCA factors. $(\omega^{\text{I-GAN}}, \beta^{\text{I-GAN}})$ uses the GAN framework to estimate the SDF weights of IPCA factors and the SDF loading. $(\omega^{\text{I-SR}}, \beta^{\text{I-FFN}})$ is the unconditional mean-variance efficient combination of IPCA factors with flexible SDF weights. $(\omega^{\text{I-SR}}, \beta^{\text{I-SR}})$ restricts those weights to be linear. $(\omega^{\text{I-XS}}, \beta^{\text{I-EV}})$ combines the IPCA factors to maximize EV while $(\omega^{\text{I-XS}}, \beta^{\text{I-XS}})$ maximizes XS-R^2. The multi-factor representation obtains the residuals with a cross-sectional regression on the multiple loadings. The SDF weights and loadings are estimated on the training data and tuning parameters are chosen optimally on the validation data set.

Table IA.XI: IPCA Max XS-R^2

	3	4	5	6	7	8	9	10
SR Train	0.05	0.56	0.47	1.10	1.03	1.07	0.99	0.95
SR Valid	0.00	0.34	0.25	0.70	0.63	0.65	0.64	0.69
SR Test	-0.06	0.15	0.12	0.41	0.33	0.37	0.34	0.41
EV Train	0.01	-0.01	-0.01	-0.04	-0.03	-0.04	-0.04	-0.05
EV Valid	-0.01	0.00	0.00	-0.02	-0.01	-0.02	-0.01	-0.02
EV Test	-0.02	-0.01	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02
XS-R^2 Train	0.13	0.21	0.20	0.29	0.30	0.31	0.30	0.31
XS-R^2 Valid	-0.04	0.12	0.11	0.22	0.20	0.20	0.22	0.24
XS-R^2 Test	-0.03	0.07	0.06	0.12	0.12	0.13	0.13	0.14

This table shows the asset pricing results for different SDFs based on IPCA. We consider $K = 3$ to 10 IPCA factors. $(\omega^{\text{I-GAN}}, \beta^{\text{I-GAN}})$ uses the GAN framework to estimate the SDF weights of IPCA factors and the SDF loading. $(\omega^{\text{I-SR}}, \beta^{\text{I-FFN}})$ is the unconditional mean-variance efficient combination of IPCA factors with flexible SDF weights. $(\omega^{\text{I-SR}}, \beta^{\text{I-SR}})$ restricts those weights to be linear. $(\omega^{\text{I-XS}}, \beta^{\text{I-EV}})$ combines the IPCA factors to maximize EV while $(\omega^{\text{I-XS}}, \beta^{\text{I-XS}})$ maximizes XS-R^2. The multi-factor representation obtains the residuals with a cross-sectional regression on the multiple loadings. The SDF weights and loadings are estimated on the training data and tuning parameters are chosen optimally on the validation data set.

Table IA.XII: IPCA Multi-Factor

	3	4	5	6	7	8	9	10
SR Train	1.59	1.67	1.78	1.82	1.85	1.88	1.88	1.95
SR Valid	1.12	1.27	1.37	1.42	1.42	1.42	1.45	1.50
SR Test	0.69	0.79	0.82	0.84	0.83	0.86	0.86	0.94
EV Train	0.06	0.07	0.08	0.08	0.08	0.09	0.09	0.09
EV Valid	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.04
EV Test	0.05	0.05	0.06	0.06	0.06	0.06	0.06	0.07
XS-R^2 Train	0.04	0.04	0.05	0.06	0.06	0.06	0.07	0.07
XS-R^2 Valid	0.04	0.05	0.06	0.07	0.06	0.06	0.06	0.06
XS-R^2 Test	-0.04	-0.03	-0.02	-0.01	-0.02	-0.01	-0.02	-0.02

This table shows the asset pricing results for different SDFs based on IPCA. We consider $K = 3$ to 10 IPCA factors. $(\omega^{\text{I-GAN}}, \beta^{\text{I-GAN}})$ uses the GAN framework to estimate the SDF weights of IPCA factors and the SDF loading. $(\omega^{\text{I-SR}}, \beta^{\text{I-FFN}})$ is the unconditional mean-variance efficient combination of IPCA factors with flexible SDF weights. $(\omega^{\text{I-SR}}, \beta^{\text{I-SR}})$ restricts those weights to be linear. $(\omega^{\text{I-XS}}, \beta^{\text{I-EV}})$ combines the IPCA factors to maximize EV while $(\omega^{\text{I-XS}}, \beta^{\text{I-XS}})$ maximizes XS-R^2. The multi-factor representation obtains the residuals with a cross-sectional regression on the multiple loadings. The SDF weights and loadings are estimated on the training data and tuning parameters are chosen optimally on the validation data set.

IA.I. Additional Empirical Results

IA.I.1. Asset Pricing on Sorted Portfolios for Additional Characteristics

Table IA.XIII: Explained Variation and Pricing Errors for Double-Sorted Portfolios based on Size and Dividend Yield

		EN	FFN	GAN	EN	FFN	GAN
LME	D2P	Explained Variation			Alpha		
1	1	0.82	0.78	0.83	-0.01	-0.01	-0.02
1	2	0.79	0.72	0.78	0.01	0.01	-0.01
1	3	0.74	0.71	0.77	0.04	0.02	-0.00
1	4	0.29	0.30	0.31	0.09	0.04	0.07
1	5	0.21	0.13	0.44	-0.10	-0.11	-0.04
2	1	0.82	0.51	0.83	-0.03	0.06	-0.01
2	2	0.81	0.56	0.85	0.01	0.08	0.01
2	3	0.72	0.54	0.78	-0.01	0.05	-0.01
2	4	0.61	0.52	0.60	-0.04	-0.03	-0.07
2	5	0.51	0.58	0.67	-0.07	-0.06	-0.03
3	1	0.73	0.46	0.81	0.09	0.15	0.06
3	2	0.76	0.54	0.84	0.04	0.11	0.02
3	3	0.70	0.51	0.83	0.09	0.15	0.06
3	4	0.77	0.69	0.83	0.05	0.07	0.02
3	5	0.67	0.70	0.70	-0.05	-0.04	-0.03
4	1	0.62	0.47	0.80	0.12	0.14	0.04
4	2	0.67	0.58	0.83	0.08	0.09	0.01
4	3	0.59	0.52	0.79	0.10	0.10	0.02
4	4	0.77	0.78	0.78	0.03	-0.00	-0.02
4	5	0.56	0.54	0.54	-0.07	-0.09	-0.07
5	1	0.15	0.35	0.53	0.11	0.07	0.01
5	2	0.23	0.39	0.60	0.09	0.05	0.00
5	3	0.23	0.21	0.51	0.03	-0.05	-0.06
5	4	0.40	0.22	0.36	-0.03	-0.09	-0.06
5	5	0.36	0.38	0.43	-0.00	-0.06	-0.03
		Explained Variation			Cross-Sectional R^2		
All		0.58	0.50	0.67	0.89	0.84	0.96

This table shows the out-of-sample explained variation and pricing errors for decile sorted portfolios based on Size (`LME`) and Dividend Yield (`D2P`).

Table IA.XIV: Explained Variation and Pricing Errors for Decile Sorted Portfolios based on Standard Unexplained Volume

SUV	EN	FFN	GAN	EN	FFN	GAN
Decile	Explained Variation			Alpha		
1	-0.22	0.50	0.78	0.28	0.00	-0.06
2	-0.03	0.64	0.82	0.33	0.10	0.03
3	0.11	0.69	0.80	0.26	0.06	0.02
4	0.28	0.71	0.80	0.21	0.03	-0.01
5	0.49	0.79	0.83	0.16	0.02	0.01
6	0.58	0.84	0.87	0.10	-0.04	-0.04
7	0.72	0.84	0.86	0.11	0.00	0.03
8	0.78	0.82	0.85	0.03	-0.01	0.01
9	0.76	0.78	0.83	-0.03	-0.09	-0.02
10	0.76	0.83	0.85	-0.13	-0.06	-0.00
	Explained Variation			Cross-Sectional R^2		
All	0.42	0.75	0.83	0.64	0.97	0.99

This table shows the out-of-sample explained variation and pricing errors for decile sorted portfolios based on Standard Unexplained Volume (`SUV`).

Table IA.XV: Explained Variation and Pricing Errors for Decile Sorted Portfolios based on Net Operating Assets

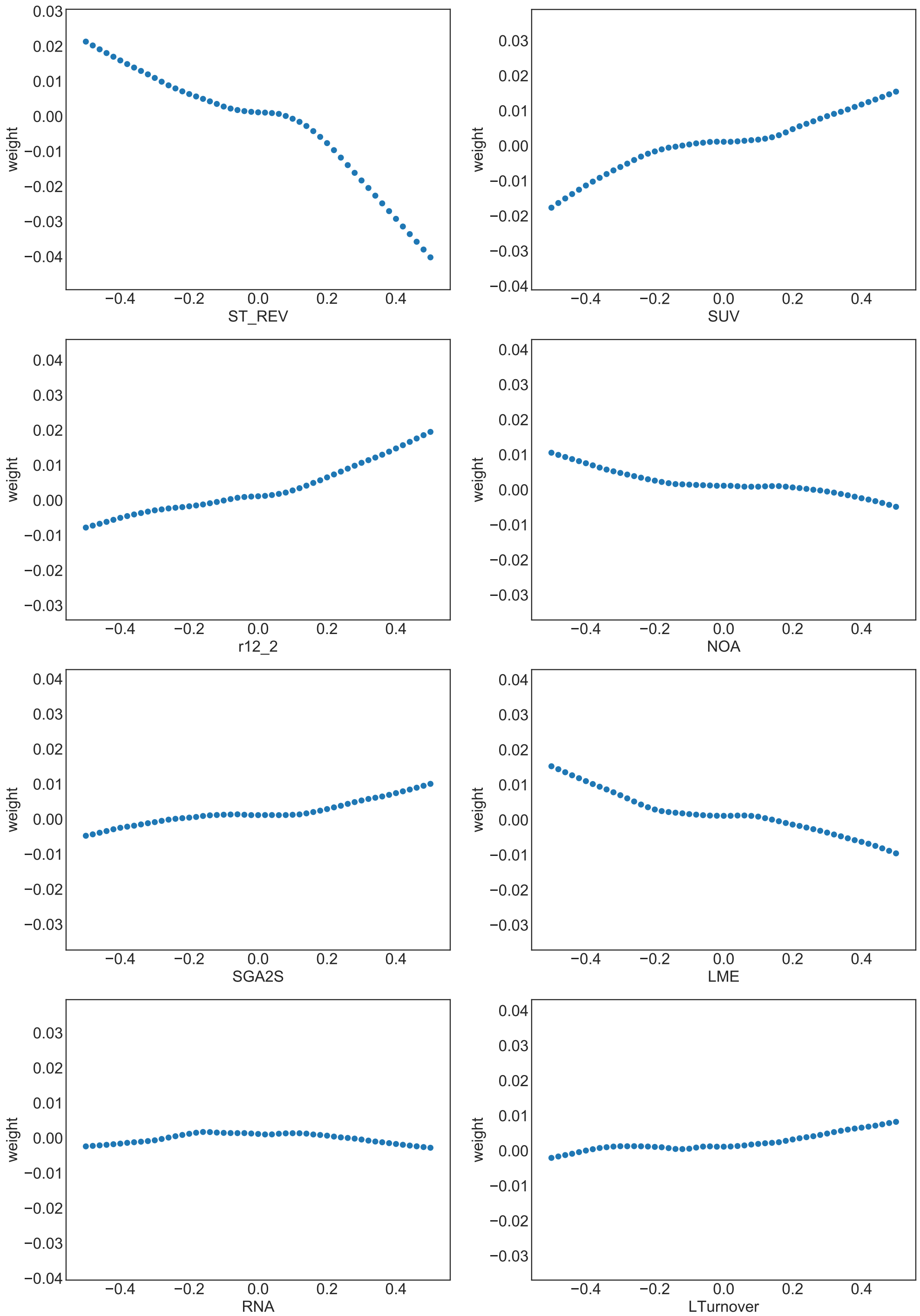
NOA	EN	FFN	GAN	EN	FFN	GAN
Decile	Explained Variation			Alpha		
1	0.41	0.55	0.66	0.17	0.10	0.09
2	0.57	0.72	0.80	0.05	-0.01	0.04
3	0.58	0.79	0.84	-0.06	-0.07	-0.03
4	0.69	0.76	0.78	0.02	0.01	0.05
5	0.73	0.75	0.77	-0.03	-0.04	0.00
6	0.64	0.75	0.75	0.06	0.03	0.05
7	0.72	0.82	0.83	0.02	-0.01	-0.00
8	0.67	0.75	0.84	-0.08	-0.12	-0.13
9	0.66	0.79	0.85	0.10	0.07	0.02
10	0.43	0.47	0.75	-0.04	-0.06	-0.15
	Explained Variation			Cross-Sectional R^2		
All	0.58	0.69	0.78	0.94	0.96	0.95

This table shows the out-of-sample explained variation and pricing errors for decile sorted portfolios based on Net Operating Assets (`NOA`).

IA.I.2. SDF Structure for Additional Characteristics

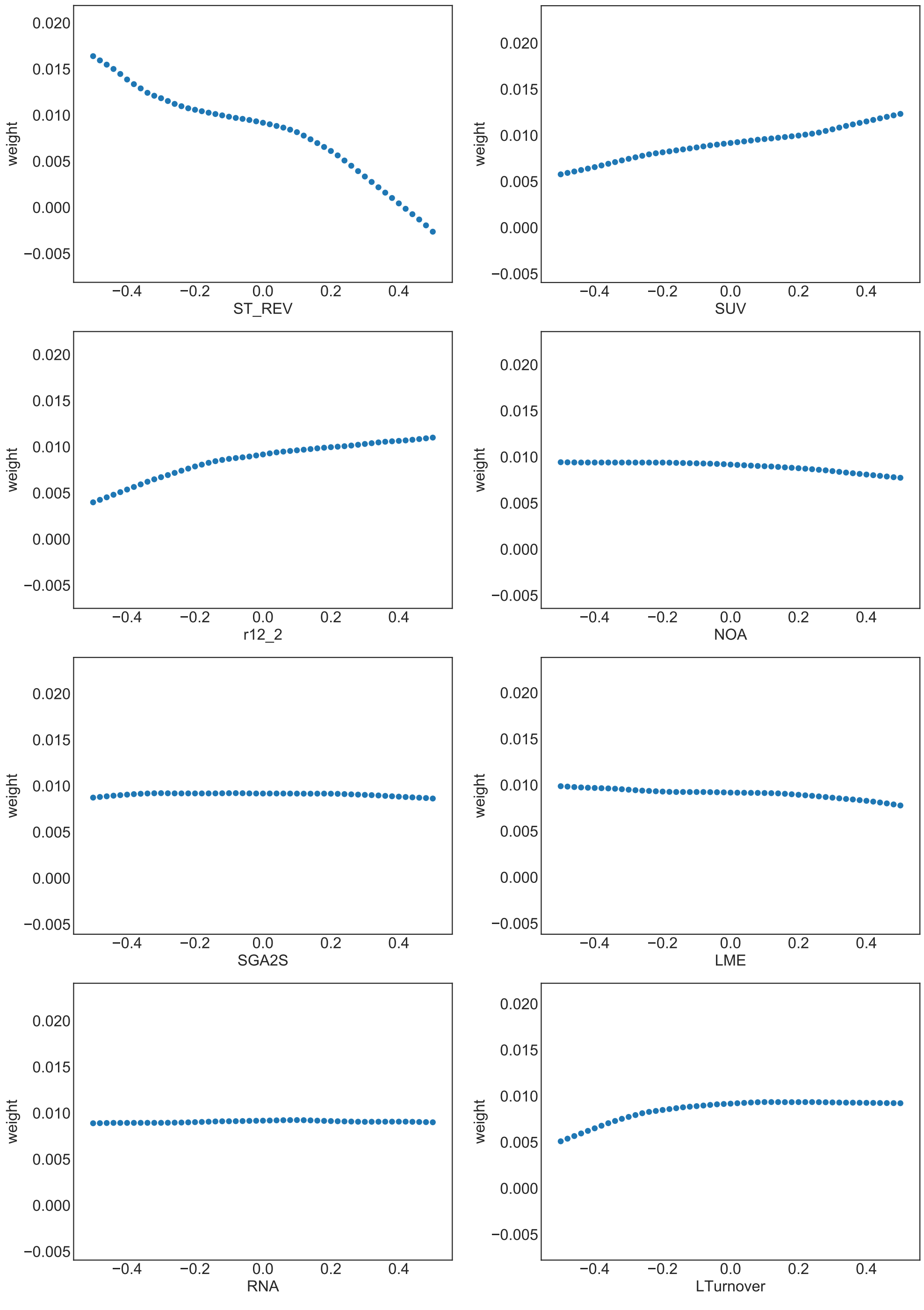
IA.I.2.1. One-Dimensional Relationship

Figure IA.25: SDF weight ω as a Function of Characteristics for GAN



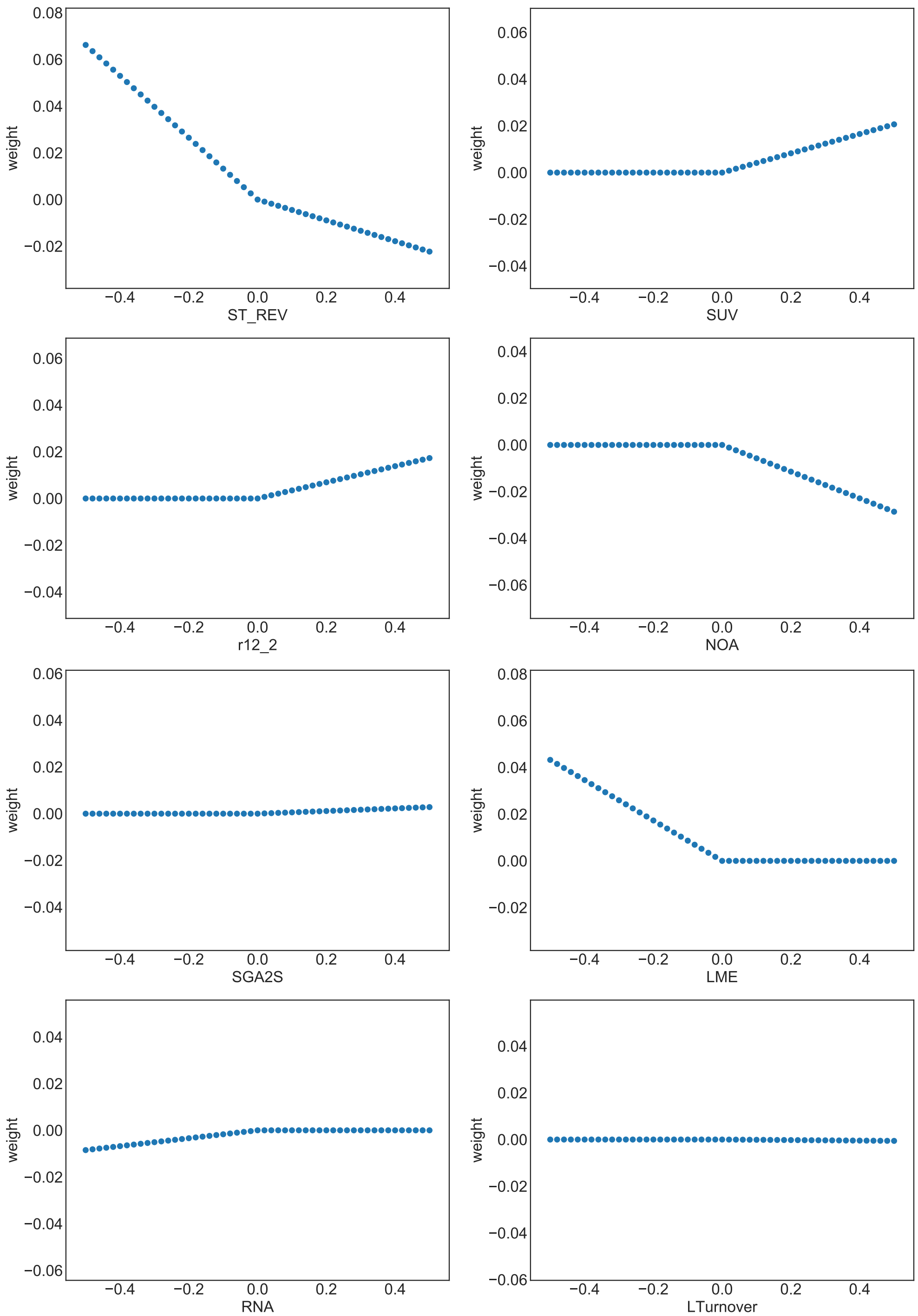
This figure shows the SDF weight ω as a one-dimensional function of characteristics keeping the other covariates at their mean level. The characteristics are Short-Term Reversal (ST_REV), Standard Unexplained Volume (SUV), Momentum (r12_2), Net Operating Assets (NOA), Selling, General and Administrative Expenses to Sales (SGA2S), Size (LME), Return on Net Operating Assets (RNA) and Turnover (LTurnover).

Figure IA.26: SDF weight ω as a Function of Characteristics for FFN



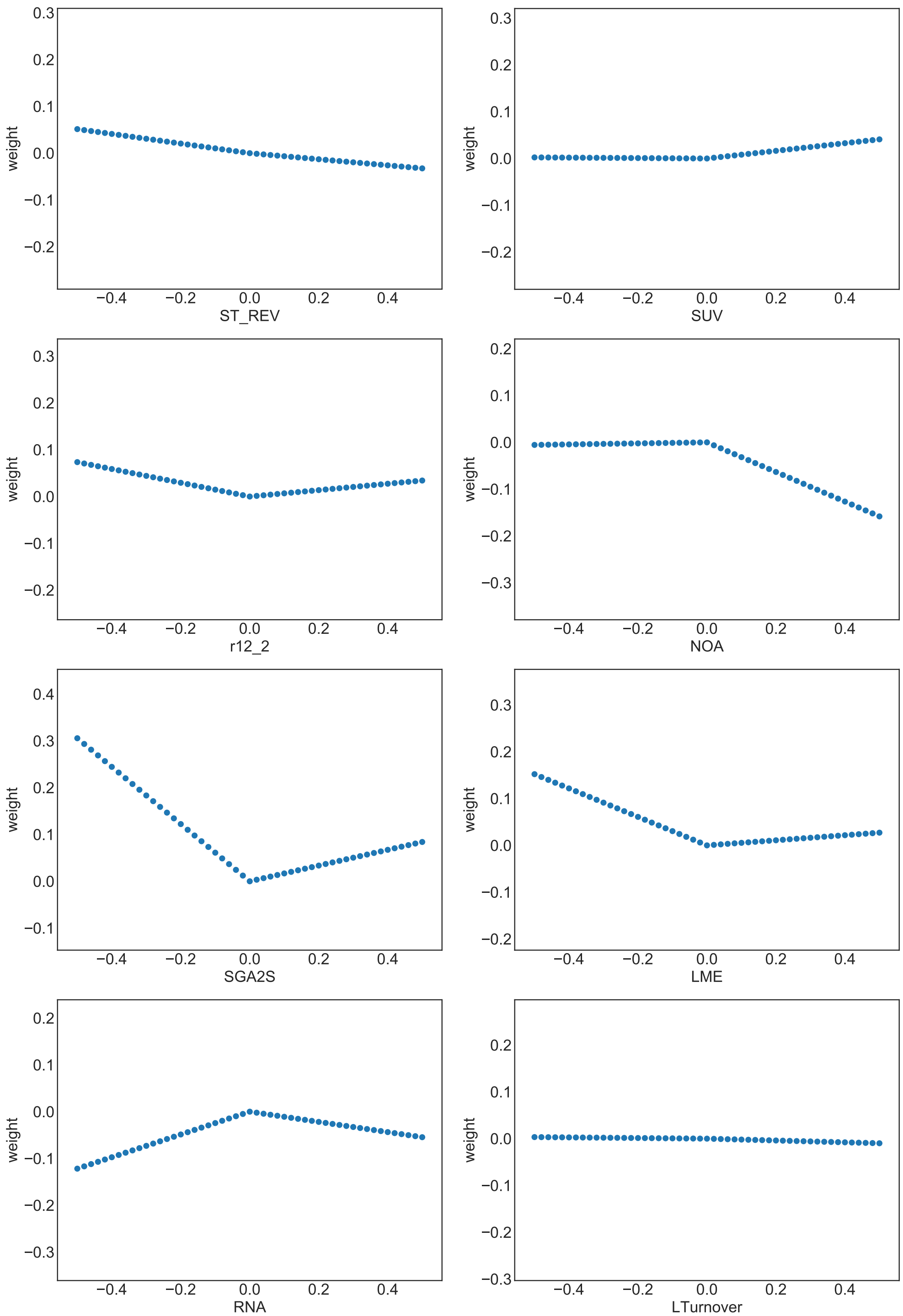
This figure shows the SDF weight ω as a one-dimensional function of characteristics keeping the other covariates at their mean level. The characteristics are Short-Term Reversal (`ST_REV`), Standard Unexplained Volume (`SUV`), Momentum (`r12_2`), Net Operating Assets (`NOA`), Selling, General and Administrative Expenses to Sales (`SGA2S`), Size (`LME`), Return on Net Operating Assets (`RNA`) and Turnover (`LTurnover`).

Figure IA.27: SDF weight ω as a Function of Characteristics for EN



This figure shows the SDF weight ω as a one-dimensional function of characteristics keeping the other covariates at their mean level. The characteristics are Short-Term Reversal (`ST_REV`), Standard Unexplained Volume (`SUV`), Momentum (`r12_2`), Net Operating Assets (`NOA`), Selling, General and Administrative Expenses to Sales (`SGA2S`), Size (`LME`), Return on Net Operating Assets (`RNA`) and Turnover (`LTurnover`).

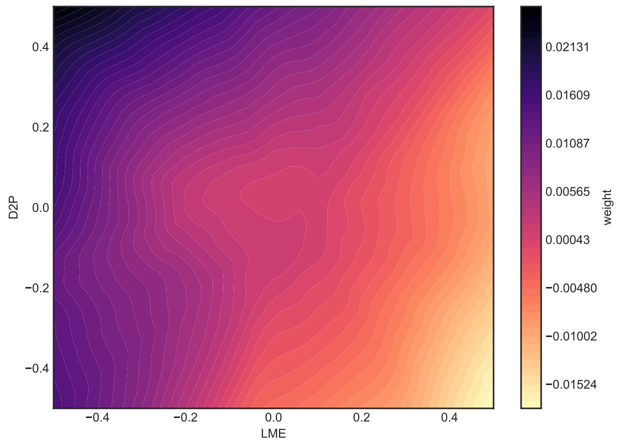
Figure IA.28: SDF weight ω as a Function of Characteristics for LS



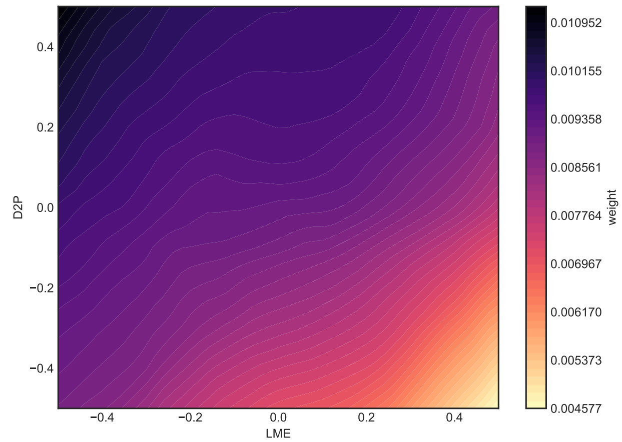
This figure shows the SDF weight ω as a one-dimensional function of characteristics keeping the other covariates at their mean level. The characteristics are Short-Term Reversal (`ST_REV`), Standard Unexplained Volume (`SUV`), Momentum (`r12_2`), Net Operating Assets (`NOA`), Selling, General and Administrative Expenses to Sales (`SGA2S`), Size (`LME`), Return on Net Operating Assets (`RNA`) and Turnover (`LTurnover`).

IA.I.2.2. Interaction between Characteristics

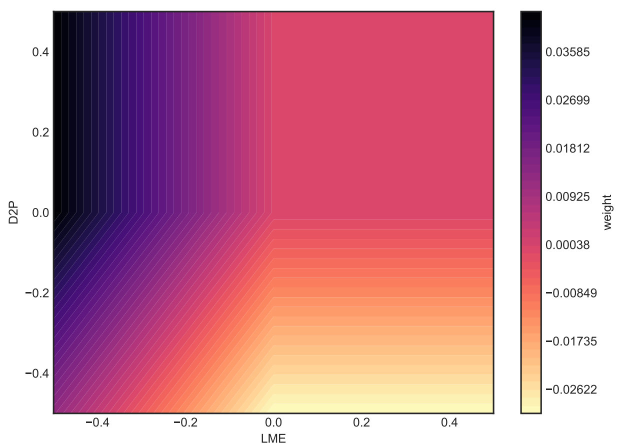
Figure IA.29: SDF weight ω as a Function of Size (`LME`) and Dividend Yield (`D2P`)



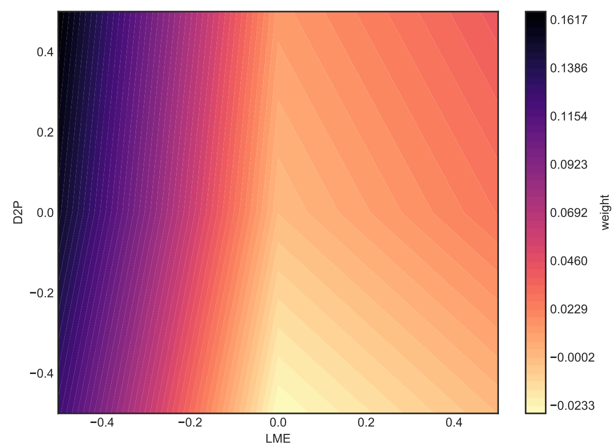
(a) GAN



(b) FFN



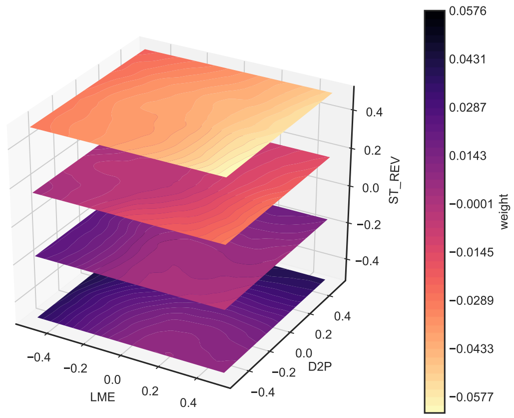
(c) EN



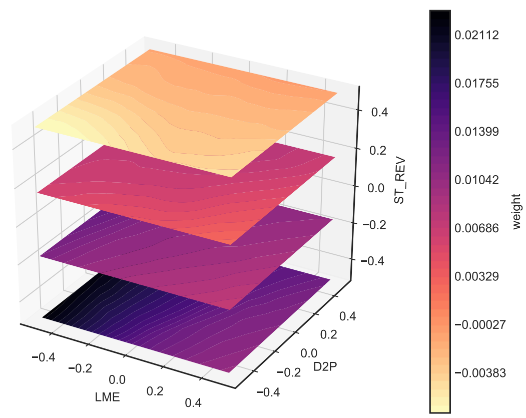
(d) LS

These figures show the SDF weight ω as two-dimensional function of characteristics keeping the remaining variables at their mean level. The two characteristics are Size (`LME`) and Dividend Yield (`D2P`).

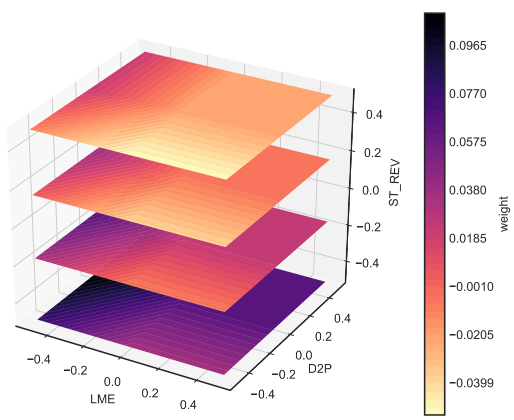
Figure IA.30: SDF weight ω as a Function of Size (`LME`), Dividend Yield (`D2P`) and Short-Term Reversal (`ST_REV`)



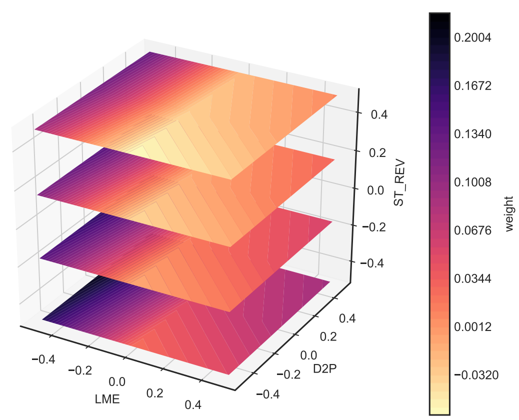
(a) GAN



(b) FFN



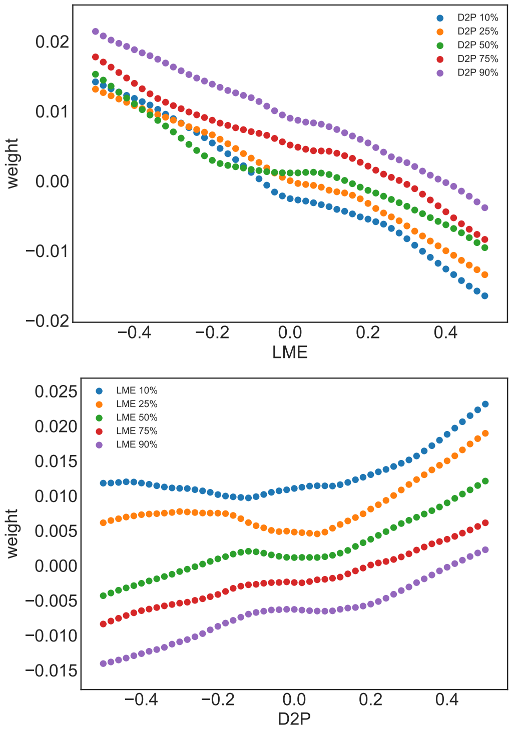
(c) EN



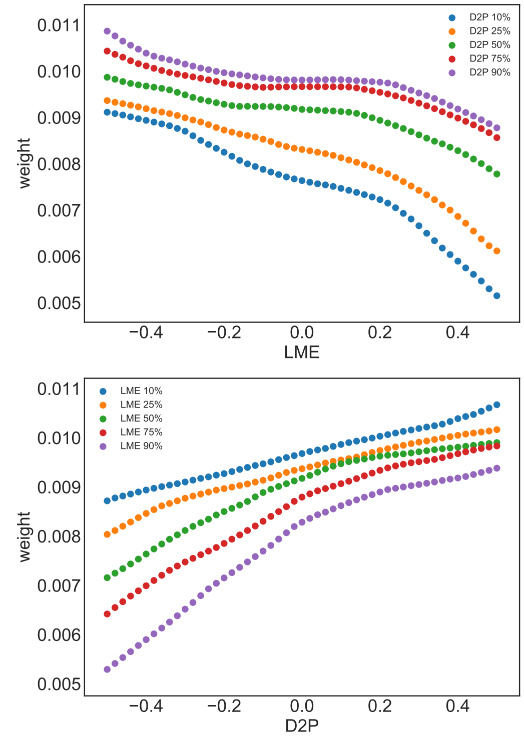
(d) LS

These figures show the SDF weight ω as three-dimensional function of characteristics keeping the remaining variables at their mean level. The two characteristics are Size (`LME`), Dividend Yield (`D2P`) and Short-Term Reversal (`ST_REV`).

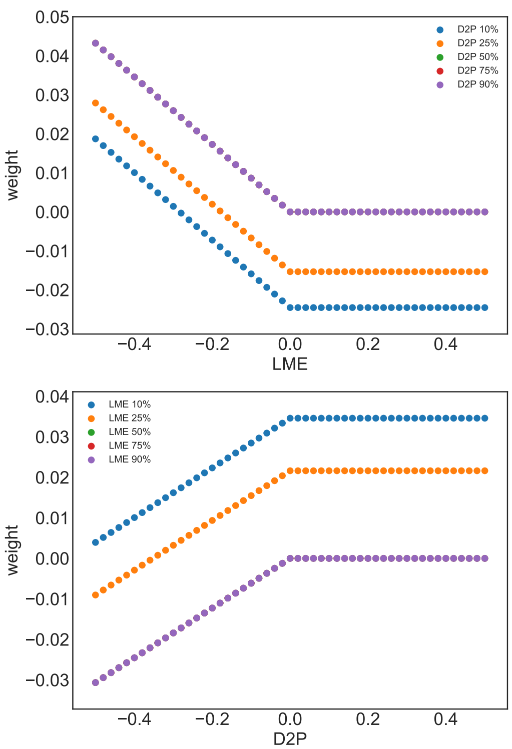
Figure IA.31: SDF weight ω as a Function of Size (`LME`) and Dividend Yield (`D2P`)



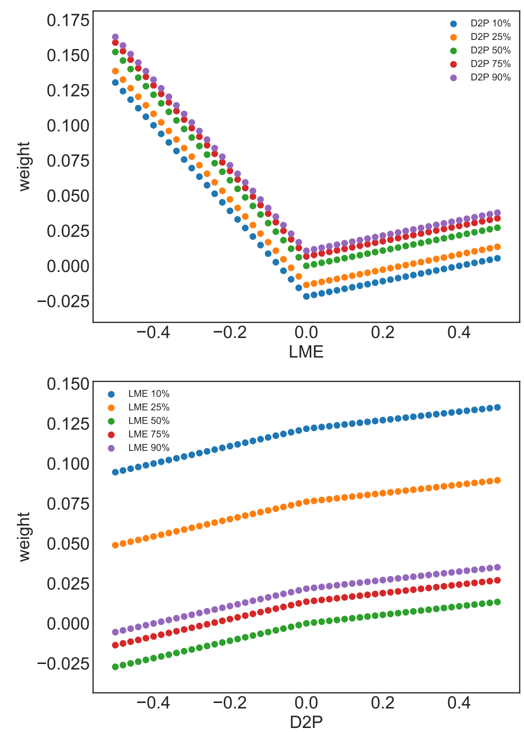
(a) GAN



(b) FFN



(c) EN



(d) LS

This figures show the SDF weight ω as function of Size (`LME`) and Dividend Yield (`D2P`) for different quantiles of the second variable while keeping the remaining variables at their mean level.

IA.J. Data

IA.J.1. List of Macroeconomic Variables

Table IA.XVI: Macroeconomic Variables

Variable Name	Description	Source	tCode
RPI	Real Personal Income	Fred-MD	5
W875RX1	Real personal income ex transfer receipts	Fred-MD	5
DPCERA3M086SBEA	Real personal consumption expenditures	Fred-MD	5
CMRMTSPLx	Real Manu. and Trade Industries Sales	Fred-MD	5
RETAILx	Retail and Food Services Sales	Fred-MD	5
INDPRO	IP Index	Fred-MD	5
IPFPNSS	IP: Final Products and Nonindustrial Supplies	Fred-MD	5
IPFINAL	IP: Final Products (Market Group)	Fred-MD	5
IPCONGD	IP: Consumer Goods	Fred-MD	5
IPDCONGD	IP: Durable Consumer Goods	Fred-MD	5
IPNCONGD	IP: Nondurable Consumer Goods	Fred-MD	5
IPBUSEQ	IP: Business Equipment	Fred-MD	5
IPMAT	IP: Materials	Fred-MD	5
IPDMAT	IP: Durable Materials	Fred-MD	5
IPNMAT	IP: Nondurable Materials	Fred-MD	5
IPMANSICS	IP: Manufacturing (SIC)	Fred-MD	5
IPB51222S	IP: Residential Utilities	Fred-MD	5
IPFUELS	IP: Fuels	Fred-MD	5
CUMFNS	Capacity Utilization: Manufacturing	Fred-MD	2
HWI	Help-Wanted Index for United States	Fred-MD	2
HWIURATIO	Ratio of Help Wanted/No. Unemployed	Fred-MD	2
CLF16OV	Civilian Labor Force	Fred-MD	5
CE16OV	Civilian Employment	Fred-MD	5
UNRATE	Civilian Unemployment Rate	Fred-MD	2
UEMPMEAN	Average Duration of Unemployment (Weeks)	Fred-MD	2
UEMPLT5	Civilians Unemployed - Less Than 5 Weeks	Fred-MD	5
UEMP5TO14	Civilians Unemployed for 5-14 Weeks	Fred-MD	5
UEMP15OV	Civilians Unemployed - 15 Weeks & Over	Fred-MD	5
UEMP15T26	Civilians Unemployed for 15-26 Weeks	Fred-MD	5
UEMP27OV	Civilians Unemployed for 27 Weeks and Over	Fred-MD	5
CLAIMSx	Initial Claims	Fred-MD	5
PAYEMS	All Employees: Total nonfarm	Fred-MD	5
USGOOD	All Employees: Goods-Producing Industries	Fred-MD	5
CES1021000001	All Employees: Mining and Logging: Mining	Fred-MD	5
USCONS	All Employees: Construction	Fred-MD	5
MANEMP	All Employees: Manufacturing	Fred-MD	5
DMANEMP	All Employees: Durable goods	Fred-MD	5
NDMANEMP	All Employees: Nondurable goods	Fred-MD	5
SRVPRD	All Employees: Service-Providing Industries	Fred-MD	5
USTPU	All Employees: Trade, Transportation & Utilities	Fred-MD	5
USWTRADE	All Employees: Wholesale Trade	Fred-MD	5
USTRADE	All Employees: Retail Trade	Fred-MD	5
USFIRE	All Employees: Financial Activities	Fred-MD	5
USGOVT	All Employees: Government	Fred-MD	5
CES0600000007	Avg Weekly Hours : Goods-Producing	Fred-MD	1
AWOTMAN	Avg Weekly Overtime Hours : Manufacturing	Fred-MD	2
AWHMAN	Avg Weekly Hours : Manufacturing	Fred-MD	1
HOUST	Housing Starts: Total New Privately Owned	Fred-MD	4
HOUSTNE	Housing Starts, Northeast	Fred-MD	4
HOUSTMW	Housing Starts, Midwest	Fred-MD	4
HOUSTS	Housing Starts, South	Fred-MD	4
HOUSTW	Housing Starts, West	Fred-MD	4
PERMIT	New Private Housing Permits (SAAR)	Fred-MD	4
PERMITNE	New Private Housing Permits, Northeast (SAAR)	Fred-MD	4
PERMITMW	New Private Housing Permits, Midwest (SAAR)	Fred-MD	4
PERMITS	New Private Housing Permits, South (SAAR)	Fred-MD	4
PERMITW	New Private Housing Permits, West (SAAR)	Fred-MD	4
AMDMNOx	New Orders for Durable Goods	Fred-MD	5
AMDMUOx	Unfilled Orders for Durable Goods	Fred-MD	5
BUSINVx	Total Business Inventories	Fred-MD	5
ISRATIOx	Total Business: Inventories to Sales Ratio	Fred-MD	2
M1SL	M1 Money Stock	Fred-MD	6
M2SL	M2 Money Stock	Fred-MD	6
M2REAL	Real M2 Money Stock	Fred-MD	5
AMBSL	St. Louis Adjusted Monetary Base	Fred-MD	6

Variable Name	Description	Source	tCode
TOTRESNS	Total Reserves of Depository Institutions	Fred-MD	6
NONBORRES	Reserves Of Depository Institutions	Fred-MD	7
BUSLOANS	Commercial and Industrial Loans	Fred-MD	6
REALLN	Real Estate Loans at All Commercial Banks	Fred-MD	6
NONREVSL	Total Nonrevolving Credit	Fred-MD	6
CONSPI	Nonrevolving consumer credit to Personal Income	Fred-MD	2
S&P 500	S&P's Common Stock Price Index: Composite	Fred-MD	5
S&P: indust	S&P's Common Stock Price Index: Industrials	Fred-MD	5
S&P div yield	S&P's Composite Common Stock: Dividend Yield	Fred-MD	2
S&P PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio	Fred-MD	5
FEDFUNDS	Effective Federal Funds Rate	Fred-MD	2
CP3Mx	3-Month AA Financial Commercial Paper Rate	Fred-MD	2
TB3MS	3-Month Treasury Bill	Fred-MD	2
TB6MS	6-Month Treasury Bill	Fred-MD	2
GS1	1-Year Treasury Rate	Fred-MD	2
GS5	5-Year Treasury Rate	Fred-MD	2
GS10	10-Year Treasury Rate	Fred-MD	2
AAA	Moody's Seasoned Aaa Corporate Bond Yield	Fred-MD	2
BAA	Moody's Seasoned Baa Corporate Bond Yield	Fred-MD	2
COMPAPFFx	3-Month Commercial Paper Minus FEDFUNDS	Fred-MD	1
TB3SMFFM	3-Month Treasury C Minus FEDFUNDS	Fred-MD	1
TB6SMFFM	6-Month Treasury C Minus FEDFUNDS	Fred-MD	1
T1YFFM	1-Year Treasury C Minus FEDFUNDS	Fred-MD	1
T5YFFM	5-Year Treasury C Minus FEDFUNDS	Fred-MD	1
T10YFFM	10-Year Treasury C Minus FEDFUNDS	Fred-MD	1
AAAFFM	Moody's Aaa Corporate Bond Minus FEDFUNDS	Fred-MD	1
BAAFFM	Moody's Baa Corporate Bond Minus FEDFUNDS	Fred-MD	1
EXSZUSx	Switzerland / U.S. Foreign Exchange Rate	Fred-MD	5
EXJPUSx	Japan / U.S. Foreign Exchange Rate	Fred-MD	5
EXUSUKx	U.S. / U.K. Foreign Exchange Rate	Fred-MD	5
EXCAUSx	Canada / U.S. Foreign Exchange Rate	Fred-MD	5
WPSFD49207	PPI: Finished Goods	Fred-MD	6
WPSFD49502	PPI: Finished Consumer Goods	Fred-MD	6
WPSID61	PPI: Intermediate Materials	Fred-MD	6
WPSID62	PPI: Crude Materials	Fred-MD	6
OILPRICEx	Crude Oil, spliced WTI and Cushing	Fred-MD	6
PPICMM	PPI: Metals and metal products	Fred-MD	6
CPIAUCSL	CPI : All Items	Fred-MD	6
CPIAPPSL	CPI : Apparel	Fred-MD	6
CPITRNSL	CPI : Transportation	Fred-MD	6
CPIMEDSL	CPI : Medical Care	Fred-MD	6
CUSR0000SAC	CPI : Commodities	Fred-MD	6
CUSR0000SAD	CPI : Durables	Fred-MD	6
CUSR0000SAS	CPI : Services	Fred-MD	6
CPIULFSL	CPI : All Items Less Food	Fred-MD	6
CUSR0000SA0L2	CPI : All items less shelter	Fred-MD	6
CUSR0000SA0L5	CPI : All items less medical care	Fred-MD	6
PCEPI	Personal Cons. Expend.: Chain Index	Fred-MD	6
DDURRG3M086SBEA	Personal Cons. Exp: Durable goods	Fred-MD	6
DNDGRG3M086SBEA	Personal Cons. Exp: Nondurable goods	Fred-MD	6
DSERRG3M086SBEA	Personal Cons. Exp: Services	Fred-MD	6
CES0600000008	Avg Hourly Earnings : Goods-Producing	Fred-MD	6
CES2000000008	Avg Hourly Earnings : Construction	Fred-MD	6
CES3000000008	Avg Hourly Earnings : Manufacturing	Fred-MD	6
MZMSL	MZM Money Stock	Fred-MD	6
DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding	Fred-MD	6
DTCTHFNM	Total Consumer Loans and Leases Outstanding	Fred-MD	6
INVEST	Securities in Bank Credit at All Commercial Banks	Fred-MD	6
VXOCLSx	CBOE S&P 100 Volatility Index: VXO	Fred-MD	1

Variable Name	Description	Source	tCode
A2ME	Cross sectional Median of A2ME	Calculated from Characteristics	5
AC	Cross sectional Median of AC	Calculated from Characteristics	2
AT	Cross sectional Median of AT	Calculated from Characteristics	6
ATO	Cross sectional Median of ATO	Calculated from Characteristics	5
BEME	Cross sectional Median of BEME	Calculated from Characteristics	5
Beta	Cross sectional Median of Beta	Calculated from Characteristics	1
C	Cross sectional Median of C	Calculated from Characteristics	5
CF	Cross sectional Median of CF	Calculated from Characteristics	2
CF2P	Cross sectional Median of CF2P	Calculated from Characteristics	5
CTO	Cross sectional Median of CTO	Calculated from Characteristics	5
D2A	Cross sectional Median of D2A	Calculated from Characteristics	5
D2P	Cross sectional Median of D2P	Calculated from Characteristics	2
DPI2A	Cross sectional Median of DPI2A	Calculated from Characteristics	5
E2P	Cross sectional Median of E2P	Calculated from Characteristics	5
FC2Y	Cross sectional Median of FC2Y	Calculated from Characteristics	5
IdioVol	Cross sectional Median of IdioVol	Calculated from Characteristics	5
Investment	Cross sectional Median of Investment	Calculated from Characteristics	5
Lev	Cross sectional Median of Lev	Calculated from Characteristics	5
LME	Cross sectional Median of LME	Calculated from Characteristics	6
LT_Rev	Cross sectional Median of LT_Rev	Calculated from Characteristics	2
LTurnover	Cross sectional Median of LTurnover	Calculated from Characteristics	5
MktBeta	Cross sectional Median of MktBeta	Calculated from Characteristics	1
NI	Cross sectional Median of NI	Calculated from Characteristics	1
NOA	Cross sectional Median of NOA	Calculated from Characteristics	5
OA	Cross sectional Median of OA	Calculated from Characteristics	2
OL	Cross sectional Median of OL	Calculated from Characteristics	5
OP	Cross sectional Median of OP	Calculated from Characteristics	5
PCM	Cross sectional Median of PCM	Calculated from Characteristics	5
PM	Cross sectional Median of PM	Calculated from Characteristics	5
PROF	Cross sectional Median of PROF	Calculated from Characteristics	5
Q	Cross sectional Median of Q	Calculated from Characteristics	5
r2_1	Cross sectional Median of r2_1	Calculated from Characteristics	2
r12_2	Cross sectional Median of r12_2	Calculated from Characteristics	2
r12_7	Cross sectional Median of r12_7	Calculated from Characteristics	2
r36_13	Cross sectional Median of r36_13	Calculated from Characteristics	2
Rel2High	Cross sectional Median of Rel2High	Calculated from Characteristics	5
Resid_Var	Cross sectional Median of Resid_Var	Calculated from Characteristics	5
RNA	Cross sectional Median of RNA	Calculated from Characteristics	5
ROA	Cross sectional Median of ROA	Calculated from Characteristics	5
ROE	Cross sectional Median of ROE	Calculated from Characteristics	5
S2P	Cross sectional Median of S2P	Calculated from Characteristics	5
SGA2S	Cross sectional Median of SGA2S	Calculated from Characteristics	5
Spread	Cross sectional Median of Spread	Calculated from Characteristics	5
ST_REV	Cross sectional Median of ST_REV	Calculated from Characteristics	2
SUV	Cross sectional Median of SUV	Calculated from Characteristics	1
Variance	Cross sectional Median of Variance	Calculated from Characteristics	5
dp	Divident-price ratio	Welch and Goyal (2008)	2
ep	Earnings-price ratio	Welch and Goyal (2008)	2
bm	Book-to-market ratio	Welch and Goyal (2008)	5
ntis	Net equity expansion	Welch and Goyal (2008)	2
tbl	Treasury-bill rate	Welch and Goyal (2008)	2
tms	Term spread	Welch and Goyal (2008)	1
dfy	Default spread	Welch and Goyal (2008)	2
svar	Stock variance	Welch and Goyal (2008)	5

This table reports the macroeconomic variables, their description, source and stationary transformation. The transformations (tCode) are (1) no transformation; (2) Δx_t; (3) $\Delta^2 x_t$; (4) $\log(x_t)$; (5) $\Delta \log(x_t)$; (6) $\Delta^2 \log(x_t)$; and (7) $\Delta(x_t/x_{t-1} - 1.0)$.

Table IA.XVII: List of Recessions in the United States (1967-2016)

Period Range	Duration	Description
Dec 1969 - Nov 1970	11 months	fiscal tightening, monetary tightening
Nov 1973 - Mar 1975	16 months	oil crisis (1973), stock market crash (1973-1974)
Jan 1980 - July 1980	6 months	monetary tightening
July 1981 - Nov 1982	16 months	energy crisis (1979), monetary tightening
July 1990 - Mar 1991	8 months	oil price shock (1990), debt accumulation, consumer pessimism
Mar 2001 - Nov 2001	8 months	dot-com bubble, 9/11 attacks
Dec 2007 - June 2009	18 months	subprime mortgage crisis

This table describes the NBER Recessions.

IA.J.2. List of Firm-Specific Characteristics

Table IA.XVIII: Firm-Specific Characteristics

Acronym	Name	Definition	Reference
A2ME	Assets to market cap	Total assets (AT) over market capitalization (PRC*SHROUT) as of December t-1	Bhandari (1988)
AC	Accrual	Change in operating working capital per split-adjusted share from the fiscal year end t-2 to t-1 divided by book equity (defined in BEME) per share in t-1. Operating working capital per split-adjusted share is defined as current assets (ACT) minus cash and short-term investments (CHE) minus current liabilities (LCT) minus debt in current liabilities (DLC) minus income taxes payable (TXP).	Sloan (1996)
AT	Total Assets	Total Assets (AT)	Gandhi and Lustig (2015)
ATO	Net sales over lagged net operating assets	Net sales (SALE) over lagged net operating assets. Net operating assets are the difference between operating assets and operating liabilities (defined in NOA)	Soliman (2008)
BEME	Book to Market Ratio	Book equity is shareholder equity (SH) plus deferred taxes and investment tax credit (TXDITC), minus preferred stock (PS). SH is shareholders' equity (SEQ). If missing, SH is the sum of common equity (CEQ) and preferred stock (PS). If missing, SH is the difference between total assets (AT) and total liabilities (LT). Depending on availability, we use the redemption (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for PS. The market value of equity (PRC*SHROUT) is as of December t-1.	Fama and French (1992)
Beta	CAPM Beta	Product of correlations between the excess return of stock i and the market excess return and the ratio of volatilities. We calculate volatilities from the standard deviations of daily log excess returns over a one-year horizon requiring at least 120 observations. We estimate correlations using overlapping three-day log excess returns over a five-year period requiring at least 750 non-missing observations.	Frazzini and Pedersen (2014)
C	Ratio of cash and short-term investments to total assets	Ratio of cash and short-term investments (CHE) to total assets (AT)	Palazzo (2012)
CF	Free Cash Flow to Book Value	Cash flow to book value of equity is the ratio of net income (NI), depreciation and amortization (DP), less change in working capital (WCAPCH), and capital expenditure (CAPX) over the book-value of equity (defined in BEME)	Hou, Karolyi, and Kho (2011)
CF2P	Cashflow to price	Cashflow over market capitalization (PRC*SHROUT) as of December t-1. Cashflow is defined as income before extraordinary items (IB) plus depreciation and amortization (DP) plus deferred taxes (TXDB).	Desai, Rajgopal, and Venkatachalam (2004)
CTO	Capital turnover	Ratio of net sales (SALE) to lagged total assets (AT)	Haugen and Baker (1996)
D2A	Capital intensity	Ratio of depreciation and amortization (DP) to total assets (AT)	Gorodnichenko and Weber (2016)
D2P	Dividend Yield	Total dividends (DIVAMT) paid from July of t-1 to June of t per dollar of equity (LME) in June of t	Litzenberger and Ramaswamy (1979)
DPI2A	Change in property, plants, and equipment	Changes in property, plants, and equipment (PPEGT) and inventory (INVT) over lagged total assets (TA)	Lyandres, Sun, and Zhang (2008)
E2P	Earnings to price	The earnings used in June of year t are total earnings before extraordinary items for the last fiscal year end in t-1. P (actually ME) is price times shares outstanding at the end of December of t-1.	Basu (1983)
FC2Y	Fixed costs to sales	Ratio of selling, general, and administrative expenses (XSGS), research and development expenses (XRD), and advertising expenses (XAD) to net sales (SALE)	D'Acunto, Liu, Pflueger, and Weber (2018)
IdioVol	Idiosyncratic volatility	Standard deviation of the residuals from aregression of excess returns on the Fama and French three-factor model	Ang, Hodrick, Xing, and Zhang (2006)
Investment	Investment	Change in total assets (AT) from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by t-2 total assets	Cooper, Gulen, and Schill (2008)
Lev	Leverage	Ratio of long-term debt (DLTT) and debt in current liabilities (DLC) to the sum of long-term debt, debt in current liabilities, and stockholders' equity (SEQ)	Lewellen (2015)
LME	Size	Total market capitalization at the end of the previous month defined as price times shares outstanding	Fama and French (1992)

Acronym	Name	Definition	Reference
LT_Rev	Long-term reversal	Cumulative return from 60 months before the return prediction to 13 months before	Jegadeesh and Titman (2001)
Lturnover	Turnover	Turnover is last month's volume (VOL) over shares outstanding (SHROUT)	Datar, Naik, and Radcliffe (1998)
MktBeta	Market Beta	Coefficient of the market excess return from the regression on excess returns in the past 60 months (24 months minimum)	Fama and MacBeth (1973)
NI	Net Share Issues	The change in the natural log of split-adjusted shares outstanding (CSHO*AJEX) from the fiscal yearend in t-2 to the fiscal yearend in t-1	Pontiff and Woodgate (2008)
NOA	Net operating assets	Difference between operating assets minus operating liabilities scaled by lagged total assets (AT). Operating assets are total assets (AT) minus cash and short-term investments (CHE), minus investment and other advances (IVAO). Operating liabilities are total assets (AT), minus debt in current liabilities (DLC), minus long-term debt (DLTT), minus minority interest (MIB), minus preferred stock (PSTK), minus common equity (CEQ).	Hirshleifer, Hou, Teoh, and Zhang (2004)
OA	Operating accruals	Changes in non-cash working capital minus depreciation (DP) scaled by lagged total assets (TA). Non-cash working capital is defined in Accrual (AC)	Sloan (1996)
OL	Operating leverage	Sum of cost of goods sold (COGS) and selling, general, and administrative expenses (XSGA) over total assets (AT)	Novy-Marx (2011)
OP	Operating profitability	Annual revenues (REVT) minus cost of goods sold (COGS), interest expense (TIE), and selling, general, and administrative expenses (XSGA) divided by book equity (defined in BEME)	Fama and French (2015)
PCM	Price to cost margin	Difference between net sales (SALE) and costs of goods sold (COGS) divided by net sales (SALE)	Bustamante and Donangelo (2017)
PM	Profit margin	Operating income after depreciation (OIADP) over net sales (SALE)	Soliman (2008)
PROF	Profitability	Gross profitability (GP) divided by the book value of equity (defined in BEME)	Ball, Gerakos, Linnainmaa, and Nikolaev (2015)
Q	Tobin's Q	Tobin's Q is total assets (AT), the market value of equity (SHROUT times PRC)minus cash and short-term investments (CEQ), minus deferred taxes (TXDB) scaled by total assets (AT)	Kaldor (1966)
r2_1	Short-term momentum	Lagged one-month return	Jegadeesh and Titman (1993)
r12_2	Momentum	To be included in a portfolio for month t (formed at the end of month t-1), a stock must have a price for the end of month t-13 and a good return for t-2. In addition, any missing returns from t-12 to t-3 must be -99.0, CRSP's code for a missing price. Each included stock also must have ME for the end of month t-1.	Fama and FrencH (1996)
r12_7	Intermediate momentum	Cumulative return from 12 months before the return prediction to seven months before	Novy-Marx (2012)
r36_13	Long-term momentum	Cumulative return from 36 months before the return prediction to 13 months before	Bondt and Thaler (1985)
Rel2High	Closeness to past year high	The ratio of stock price at the end of the previous calendar month and the highest daily price in the past year	George and Hwang (2004)
Resid_Var	Residual Variance	Variance of the residuals from a regression of excess returns in the past two months on the Fama and French three-factor model	Ang, Hodrick, Xing, and Zhang (2006)
RNA	Return on net operating assets	Ratio of operating income after depreciation (OIADP) to lagged net operating assets. Net operating assets are the difference between operating assets minus operating liabilities. (defined in NOA)	Soliman (2008)
ROA	Return on assets	Income before extraordinary items (IB) to lagged total assets (AT)	Balakrishnan, Bartov, and Faurel (2010)
ROE	Return on equity	Income before extraordinary items (IB) to lagged book-value of equity (defined in BEME)	Haugen and Baker (1996)
S2P	Sales to price	Ratio of net sales (SALE) to the market capitalization (LME)	Lewellen (2015)
SGA2S	Selling, general and administrative expenses to sales	Ratio of selling, general and administrative expenses (XSGA) to net sales (SALE)	Freyberger, Neuhierl, and Weber (2020)

Acronym	Name	Definition	Reference
Spread	Bid-ask spread	The average daily bid-ask spread in the previous month	Chung and Zhang (2014)
ST_Rev	Short-term reversal	Prior month return	Jegadeesh and Titman (1993)
SUV	Standard unexplained volume	Difference between actual volume and predicted volume in the previous month. Predicted volume comes from a regression of daily volume on a constant and the absolute values of positive and negative returns. Unexplained volume is standardized by the standard deviation of the residuals from the regression	Garfinkel (2009)
Variance	Variance	Variance of daily returns in the past two months	Ang, Hodrick, Xing, and Zhang (2006)

This table summarize the firm-specific characteristics. It includes their acronym, name, definition and reference. We use the same characteristics as in the 2017 paper version of Freyberger, Neuhierl, and Weber (2020) and augment them with the characteristics listed on the Kenneth French Data Library.

REFERENCES

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006): "The Cross-Section of Volatility and Expected Returns," *Journal of Finance*, 61(1), 259–299.

Balakrishnan, K., E. Bartov, and L. Faurel (2010): "Post loss/profit announcement drift," *Journal of Accounting and Economics*, 50(1), 20–41.

Ball, R., J. Gerakos, J. T. Linnainmaa, and V. V. Nikolaev (2015): "Deflating profitability," *Journal of Financial Economics*, 117(2), 225 – 248.

Basu, S. (1983): "The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence," *Journal of Financial Economics*, 12(1), 129–156.

Bhandari, L. C. (1988): "Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence," *The Journal of Finance*, 43(2), 507–528.

Bondt, W. F. M. D., and R. Thaler (1985): "Does the Stock Market Overreact?," *The Journal of Finance*, 40(3), 793–805.

Bustamante, M. C., and A. Donangelo (2017): "Product Market Competition and Industry Returns," *The Review of Financial Studies*, 30(12), 4216–4266.

Chung, K. H., and H. Zhang (2014): "A simple approximation of intraday spreads using daily data," *Journal of Financial Markets*, 17(C), 94–120.

Cooper, M. J., H. Gulen, and M. J. Schill (2008): "Asset Growth and the Cross-Section of Stock Returns," *Journal of Finance*, 63(4), 1609–1651.

D'Acunto, F., R. Liu, C. Pflueger, and M. Weber (2018): "Flexible Prices and Leverage," *Journal of Financial Economics*, 129(1), 46–68.

Datar, V. T., N. Y. Naik, and R. Radcliffe (1998): "Liquidity and stock returns: An alternative test," *Journal of Financial Markets*, 1(2), 203 – 219.

Desai, H., S. Rajgopal, and M. Venkatachalam (2004): "Value-Glamour and Accruals Mispricing: One Anomaly or Two?," *The Accounting Review*, 79(2), 355–385.

Fama, E. F., and K. R. French (1992): "The Cross-Section of Expected Stock Returns," *The Journal of Finance*, 47(2), 427–465.

Fama, E. F., and K. R. FrencH (1996): "Multifactor Explanations of Asset Pricing Anomalies," *The Journal of Finance*, 51(1), 55–84.

Fama, E. F., and K. R. French (2015): "A five-factor asset pricing model.," *Journal of Financial Economics*, 116(1), 1–22.

Fama, E. F., and J. D. MacBeth (1973): "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81(3), 607–636.

Frazzini, A., and L. H. Pedersen (2014): "Betting against beta," *Journal of Financial Economics*, 111(1), 1 – 25.

Freyberger, J., A. Neuhierl, and M. Weber (2020): "Dissecting characteristics nonparametrically," *Review of Financial Studies, forthcoming*, 33(5), 2326–2377.

Gandhi, P., and H. Lustig (2015): "Size anomalies in US bank stock returns," *Journal of Finance*, 70(2), 733–768.

Garfinkel, J. A. (2009): "Measuring Investors' Opinion Divergence," *Journal of Accounting Research*, 47(5), 1317–1348.

George, T. J., and C.-Y. Hwang (2004): "The 52-Week High and Momentum Investing," *The Journal of Finance*, 59(5), 2145–2176.

Gorodnichenko, Y., and M. Weber (2016): "Are Sticky Prices Costly? Evidence from the Stock Market," *American Economic Review*, 106(1), 165–99.

Haugen, R. A., and N. L. Baker (1996): "Commonality in the determinants of expected stock returns," *Journal of Financial Economics*, 41(3), 401 – 439.

Hirshleifer, D., K. Hou, S. H. Teoh, and Y. Zhang (2004): "Do investors overvalue firms with bloated balance sheets?," *Journal of Accounting and Economics*, 38, 297 – 331.

Hou, K., G. A. Karolyi, and B.-C. Kho (2011): "What Factors Drive Global Stock Returns?," *The Review of Financial Studies*, 24(8), 2527–2574.

Jegadeesh, N., and S. Titman (1993): "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *The Journal of Finance*, 48(1), 65–91.

——— (2001): "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations," *The Journal of Finance*, 56(2), 699–720.

Kaldor, N. (1966): "Marginal Productivity and the Macro-Economic Theories of Distribution: Comment on Samuelson and Modigliani," *The Review of Economic Studies*, 33(4), 309–319.

Lewellen, J. (2015): "The Cross-section of Expected Stock Returns," *Critical Finance Review*, 4(1), 1–44.

Litzenberger, R. H., and K. Ramaswamy (1979): "The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence," *Journal of Financial Economics*, 7(2), 163–195.

Lyandres, E., L. Sun, and L. Zhang (2008): "The New Issues Puzzle: Testing the Investment-Based Explanation," *The Review of Financial Studies*, 21(6), 2825–2855.

Novy-Marx, R. (2011): "Operating Leverage," *Review of Finance*, 15(1), 103–134.

——— (2012): "Is momentum really momentum?," *Journal of Financial Economics*, 103(3), 429–453.

Palazzo, B. (2012): "Cash holdings, risk, and expected returns," *Journal of Financial Economics*, 104(1), 162–185.

Pontiff, J., and A. Woodgate (2008): "Share issuance and cross-sectional returns," *The Journal of Finance*, 63(2), 921–945.

Sloan, R. G. (1996): "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?," *The Accounting Review*, 71(3), 289–315.

Soliman, M. T. (2008): "The Use of DuPont Analysis by Market Participants," *The Accounting Review*, 83(3), 823–853.