(Re-)Imag(in)ing Price Trends

Working paper

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Presented by: Long Zhen

Contents

Introduction – Backgrounds

- A large literature investigates the ability of past prices to forecast future returns, producing a handful of famous and robust predictors including price momentum and reversal.
- But it is difficult to see a theoretically motivated specific alternative hypothesis

Introduction – Motivation

- We reconsider the problem, and emphasize that there is potentially much to learn about the behavior of price-based predictive patterns.

→ machine learning perspective

- Represent historical prices as an image
- Convolutional neural network (CNN)

- Why CNN?
  - automatically extract predictive signals from **images**.
  - transform pixel values to predictor **values**.
- Why image?
  - To enjoy the **CNN**'s benefits of automated signal generation
  - Focus on relational attributes of the data just like **human**
  - Converts all assets' data histories to a comparable **scale**.

Introduction – Research Problem

- Can we predict equity prices based on historical data images?
- Can we transfer the model to other scales or markets?
- How to interpret the outperformance?

Introduction – Contribution

- Contribute to the technical analysis literature from a different perspective.

Research Design

→ Train CNN model to predict the direction (up/down) of future stock returns.

- Input: images depicting price and value (daily open, close, high and low prices, daily trading volume and moving average price) over the past 5, 20, and 60 days
- Output: a set of stock-level estimates for the probability of a positive subsequent return over 5, 20, and 60 days.

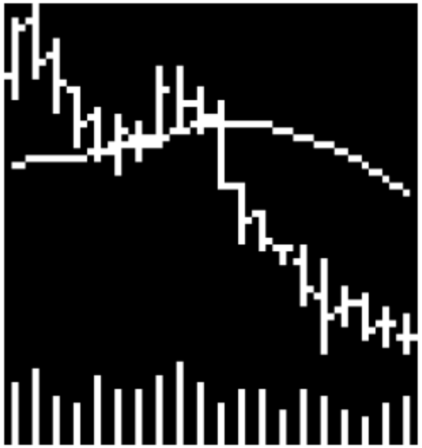
Research Design

- How to “imaging” market data?
- CNN methodology

Figure 1: Tesla OHLC Chart from Yahoo! Finance

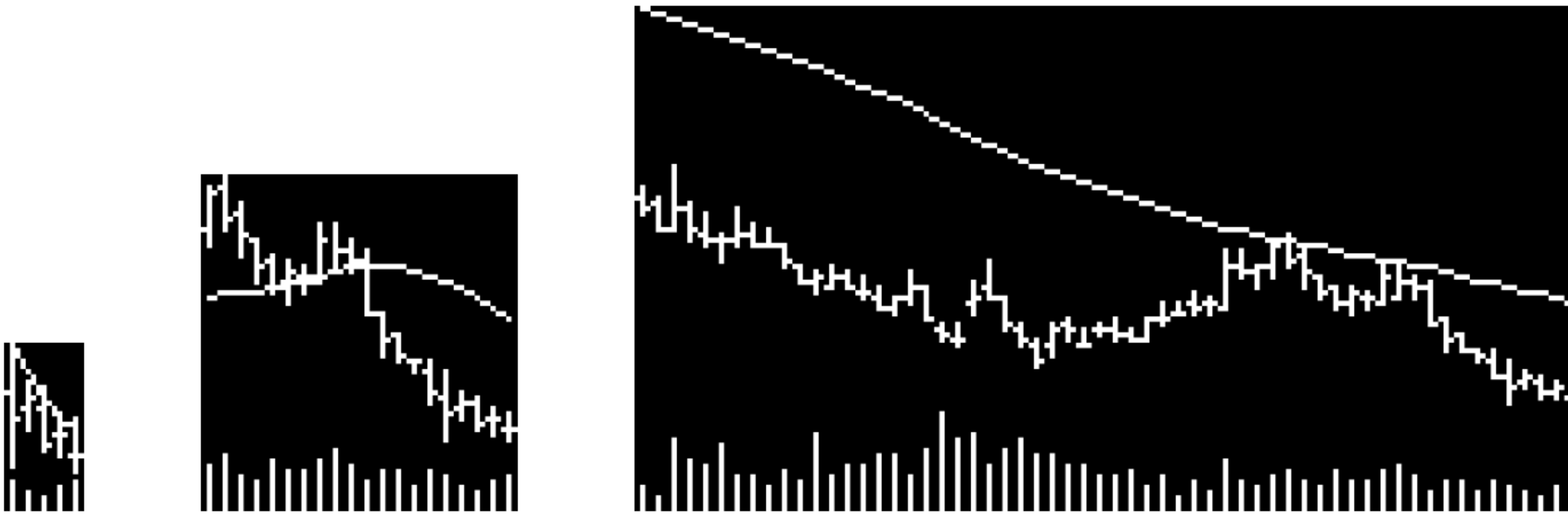
Note: OHLC chart for Tesla stock with 20-day moving average price line and daily volume bars. Daily data from January 1, 2020 to August 18, 2020.

- One day occupies an 3 pixels wide
- Once days are concatenated, we impose a constant height for all images and scale the vertical axis so that the maximum and minimum of the OHLC path coincides with the top and bottom of the image.
- use a moving average line with a window length equal to the number of days in the image
- volume is shown in the bottom one-fifth of the image



(d) w/ VB, w/ MA

Figure 4: Generated OHLC Images with Volume Bar and Moving Average Line

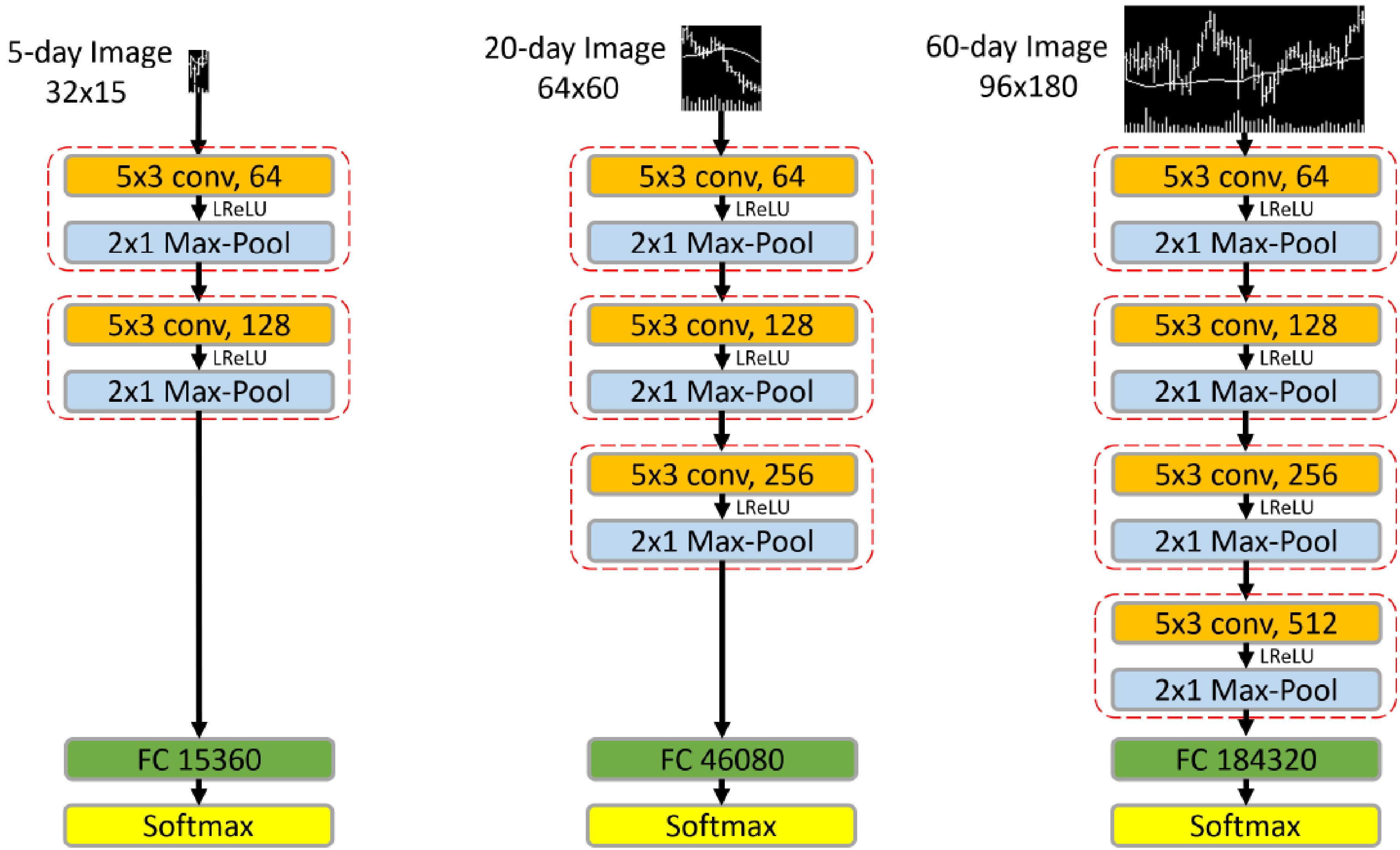


(a) 5 (b) 20 (c) 60

CNN model construction:

- Filter size: 5x3 Since our images are largely sparse in the vertical dimension
- Stride: 1 step horizontally, 3 steps vertically
- Max-pooling filter: 2x1
- The output from the last building block is flattened into a vector and each element is treated as a feature in a standard, fully connected feed-forward layer for the final prediction step. The final prediction is a linear combination of the vectorized image features, which is fed through a softmax (i.e., logistic) function to generate a probability of whether the future price will rise.

Figure 7: Diagram of CNN Models



- Data:
  - 1993~2019 CRSP
- Image labels take a value of 0/1 for +/- returns over the 20 or 60 days subsequent to the image.
- Image width(5/20/60) * return horizon(20/60)

  → 6 separately estimated models
- train and validate each model only once using data from 1993 to 2000, in which 70% of the sample are randomly selected for training and 30% for validation. The trained CNN is held fixed for the entire 2001 to 2019 test sample.

- Prediction accuracy

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN).$$

Table 2: Out-of-Sample Classification Accuracy

	Return horizon			
	20-day		60-day	
Image size	Acc.	Corr.	Acc.	Corr.
5-day	52.5%	3.1%	53.6%	2.3%
20-day	53.3%	3.4%	53.2%	2.4%
60-day	53.6%	2.9%	52.9%	3.1%
MOM	52.1%	1.8%	52.1%	1.5%
STR	50.4%	1.4%	49.8%	1.2%
WSTR	51.0%	2.8%	50.4%	2.6%

“up” prediction if it exceeds the cross-sectional median value of the signal

- MOM, STR and WSTR are statistically significant improvements over random guessing, and both are less accurate than the best CNN at each horizon

Figure 9: Prediction Accuracy By Decile

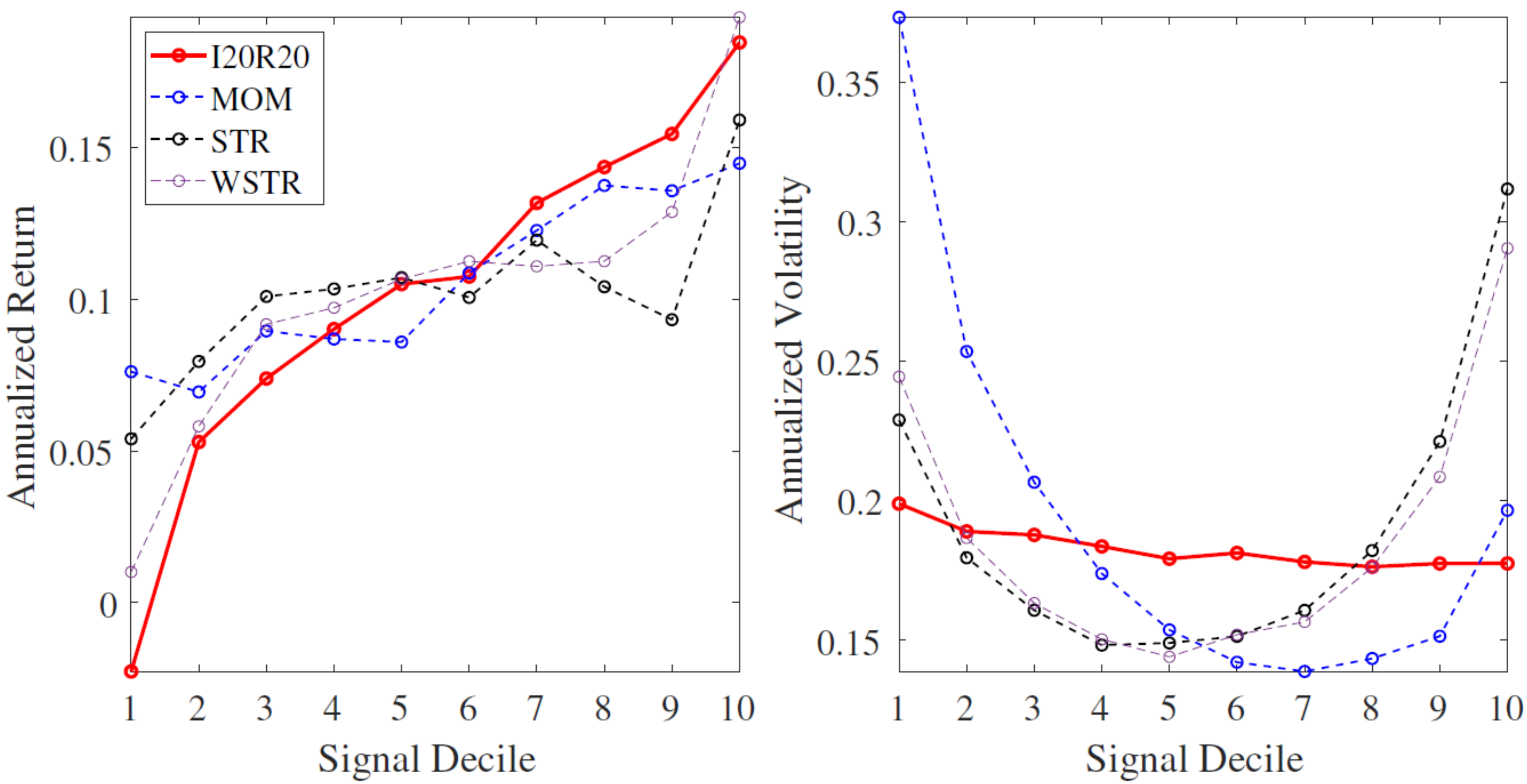


Table 3: Performance of Equal Weight Portfolios

	I5/R20		I20/R20		I60/R20		MOM/R20		STR/R20		WSTR/R20	
	Ret	SR	Ret	SR	Ret	SR	Ret	SR	Ret	SR	Ret	SR
Low	-0.00	-0.03	-0.02	-0.12	-0.02	-0.07	0.07	0.20	0.05	0.23	0.01	0.03
High	0.21	1.09	0.18	1.04	0.14	0.99	0.14	0.74	0.16	0.51	0.19	0.66
H-L	0.22***	2.35	0.21***	2.16	0.16***	1.29	0.07	0.25	0.11**	0.55	0.18***	1.23
Turnover	175%		173%		155%		63%		168%		167%	
	I5/R60		I20/R60		I60/R60		MOM/R60		STR/R60		WSTR/R60	
	Ret	SR	Ret	SR	Ret	SR	Ret	SR	Ret	SR	Ret	SR
Low	0.07	0.31	0.08	0.32	0.08	0.27	0.11	0.25	0.07	0.27	0.06	0.22
High	0.16	0.77	0.13	0.74	0.15	0.88	0.13	0.57	0.14	0.40	0.16	0.48
H-L	0.09***	1.30	0.05	0.37	0.07*	0.43	0.02	0.06	0.07	0.34	0.10***	0.65
Turnover	59%		59%		58%		37%		56%		56%	

Table 5: Exposure to Technical Analysis Factors

	Equal Weight		Value Weight	
	20-day	60-day	20-day	60-day
Mean Ret	1.73%	1.33%	0.45%	0.17%
t-stat	9.4	5.6	2.1	0.7
Alpha	1.86%	1.31%	0.82%	0.27%
t-stat	10.7	5.6	3.9	1.1
Mkt-Rf	-0.32	-0.29	-0.21	-0.16
t-stat	-7.3	-5.0	-4.0	-2.6
Momentum	0.01	0.16	0.04	0.11
t-stat	0.3	3.0	0.9	1.9
STR	-0.07	0.05	-0.09	-0.01
t-stat	-1.3	0.7	-1.4	-0.1
WSTR	0.37	0.60	-0.92	-0.10
t-stat	1.2	1.4	-2.5	-0.2
R^2	26.8%	20.7%	21.6%	9.2%

(taking the equal weighted average of all models with the same supervision window)

Table 6: Short-horizon (One Week) Portfolio Performance

	Equal Weight											
	I5/R5		I20/R5		I60/R5		MOM/R5		STR/R5		WSTR/R5	
	Ret	SR	Ret	SR	Ret	SR	Ret	SR	Ret	SR	Ret	SR
Low	-0.28	-1.92	-0.32	-1.94	-0.21	-1.10	0.15	0.44	-0.01	-0.03	-0.08	-0.34
High	0.54	2.89	0.52	2.76	0.33	1.85	0.16	0.78	0.38	1.19	0.46	1.56
H-L	0.83***	7.15	0.84***	6.75	0.54***	4.89	0.02	0.07	0.39***	1.76	0.53***	2.84
Turnover	862%		834%		774%		154%		426%		825%	

	Value Weight											
	I5/R5		I20/R5		I60/R5		MOM/R5		STR/R5		WSTR/R5	
	Ret	SR	Ret	SR	Ret	SR	Ret	SR	Ret	SR	Ret	SR
Low	-0.03	-0.19	-0.03	-0.16	-0.02	-0.12	0.03	0.06	0.04	0.16	-0.02	-0.09
High	0.20	0.91	0.20	0.99	0.14	0.77	0.14	0.63	0.16	0.46	0.18	0.59
H-L	0.23***	1.49	0.22***	1.74	0.16***	1.44	0.12	0.33	0.13*	0.44	0.21***	0.77
Turnover	947%		910%		839%		204%		541%		917%	

Table 7: Other Holding Periods Sharpe ratios

	Holding Period					
	Equal Weight			Value Weight		
Model	5 days	20 days	60 days	5 days	20 days	60 days
I5/R5	7.15	2.77	1.40	1.49	0.77	0.46
I5/R20	5.53	2.35	1.36	1.26	0.45	0.31
I5/R60	4.32	2.05	1.30	0.74	0.32	0.47
I20/R5	6.75	3.17	1.59	1.74	0.73	0.37
I20/R20	3.87	2.16	1.05	0.89	0.49	0.44
I20/R60	0.97	0.45	0.37	0.01	0.26	0.32
I60/R5	4.89	2.33	1.08	1.44	0.55	0.35
I60/R20	2.19	1.29	0.60	0.99	0.17	0.13
I60/R60	1.00	0.75	0.43	0.36	0.38	0.23

- there is no single image length, and no single supervision window, that is dominant in terms of portfolio performance across investment horizons.

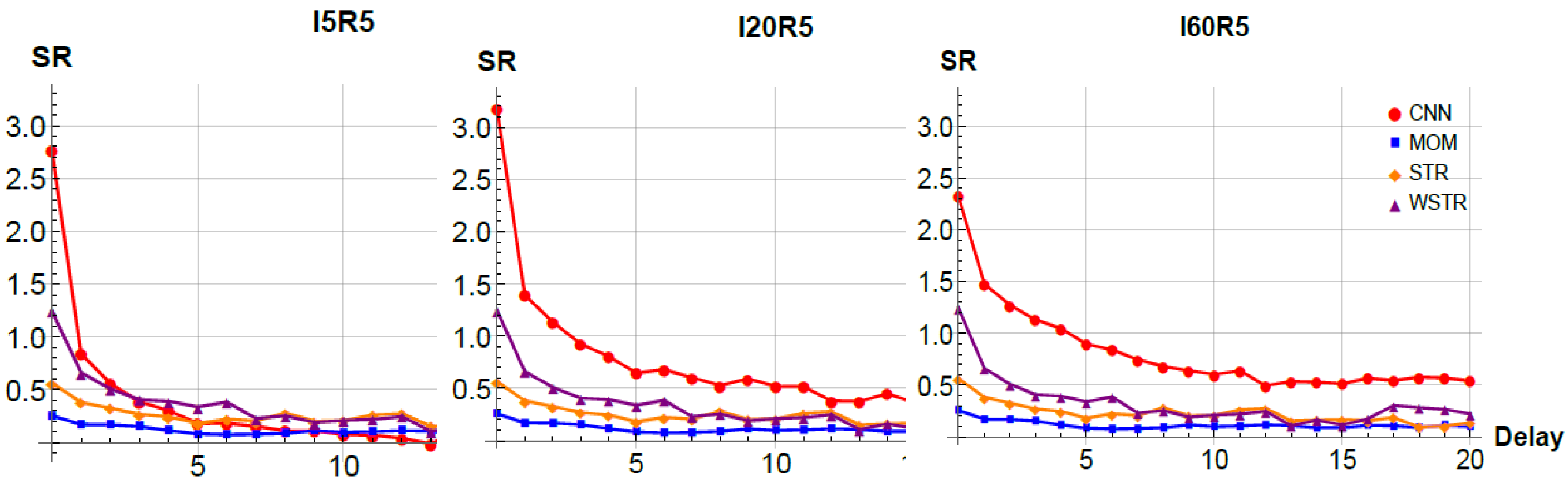
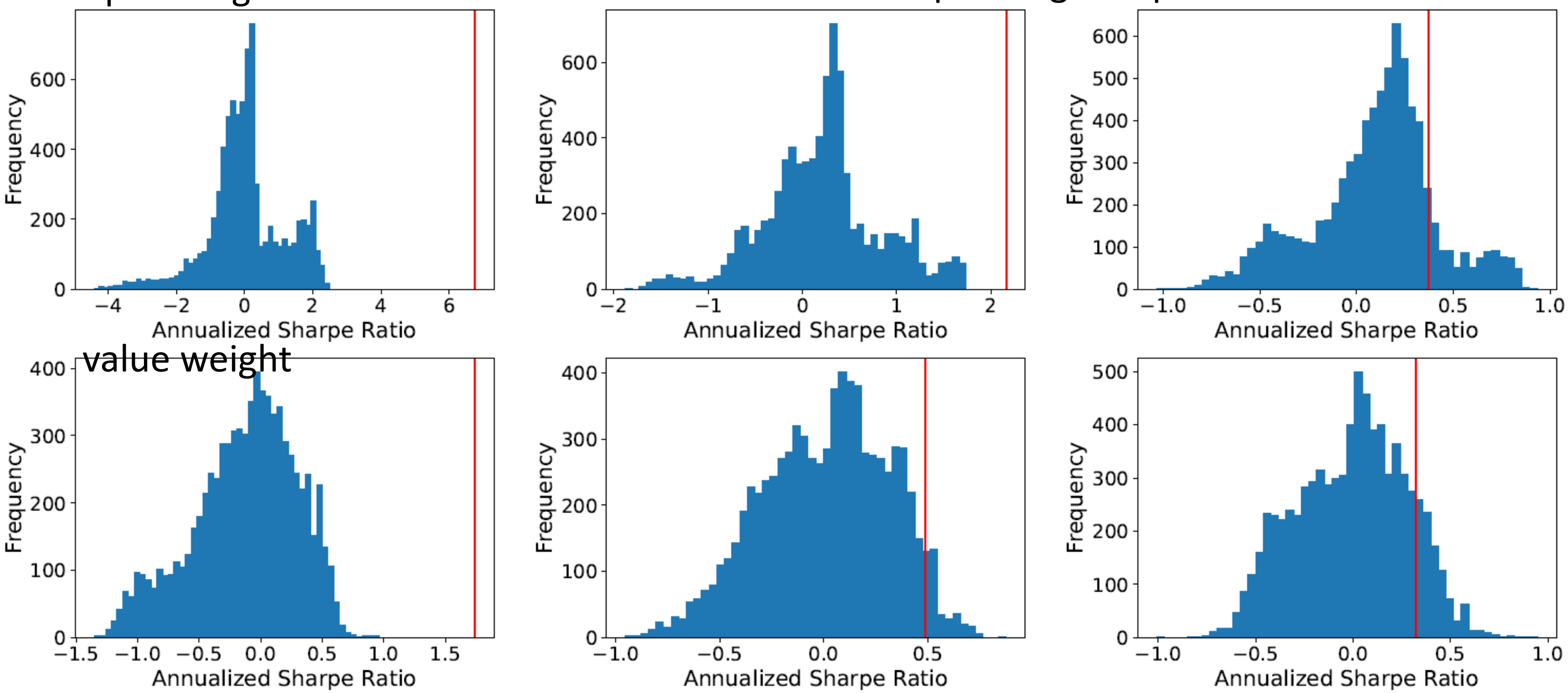

I5R5
SR
3.0
2.5
2.0
1.5
1.0
0.5
5
10
I20R5
SR
3.0
2.5
2.0
1.5
1.0
0.5
5
10
I60R5
SR
3.0
2.5
2.0
1.5
1.0
0.5
5
10
15
20
Delay
CNN
MOM
STR
WSTR

Figure 11: Comparison With Traditional Technical Indicators

equal weight

corresponding Sharpe ratios for CNN



rebalance by week

month

quarter

Transfer Learning

- Time scale transfer

Table 8: Time Scale Transfer I5/R5 to I20/R20

Panel A: Equal Weight Portfolios								
	Baseline		Re-train		Transfer		Baseline+Transfer	
	Ret	SR	Ret	SR	Ret	SR	Ret	SR
Low	-0.02	-0.12	-0.02	-0.10	-0.01	-0.07	-0.04	-0.19
2	0.05	0.28	0.05	0.26	0.04	0.25	0.04	0.20
3	0.07	0.39	0.07	0.37	0.07	0.40	0.06	0.35
4	0.09	0.49	0.09	0.49	0.08	0.43	0.08	0.44
5	0.11	0.59	0.10	0.56	0.09	0.50	0.09	0.52
6	0.11	0.59	0.11	0.61	0.10	0.53	0.11	0.64
7	0.13	0.74	0.12	0.65	0.11	0.59	0.13	0.70
8	0.14	0.81	0.14	0.79	0.14	0.70	0.15	0.80
9	0.15	0.87	0.15	0.82	0.17	0.84	0.17	0.89
High	0.18	1.04	0.20	1.15	0.24	1.14	0.23	1.17
H-L	0.21***	2.16	0.22***	2.21	0.25***	2.14	0.26***	2.46
Turnover	173%		177%		176%		175%	

Table 9: Time Scale Transfer I5/R5 to I60/R60

	Panel A: Equal Weight Portfolios							
	Baseline		Re-train		Transfer		Baseline+Transfer	
	Ret	SR	Ret	SR	Ret	SR	Ret	SR
Low	0.08	0.27	0.08	0.30	0.06	0.31	0.06	0.22
2	0.09	0.37	0.08	0.34	0.08	0.41	0.09	0.35
3	0.11	0.46	0.10	0.43	0.10	0.50	0.11	0.46
4	0.12	0.52	0.12	0.53	0.11	0.54	0.11	0.51
5	0.12	0.55	0.12	0.55	0.11	0.54	0.12	0.55
6	0.12	0.57	0.12	0.57	0.13	0.61	0.12	0.61
7	0.14	0.68	0.13	0.64	0.12	0.55	0.14	0.67
8	0.14	0.72	0.13	0.64	0.14	0.60	0.14	0.69
9	0.14	0.75	0.13	0.72	0.14	0.59	0.15	0.78
High	0.15	0.88	0.14	0.88	0.17	0.69	0.16	0.93
H-L	0.07*	0.43	0.06	0.37	0.10***	0.90	0.10***	0.81
Turnover	58%		59%		59%		58%	

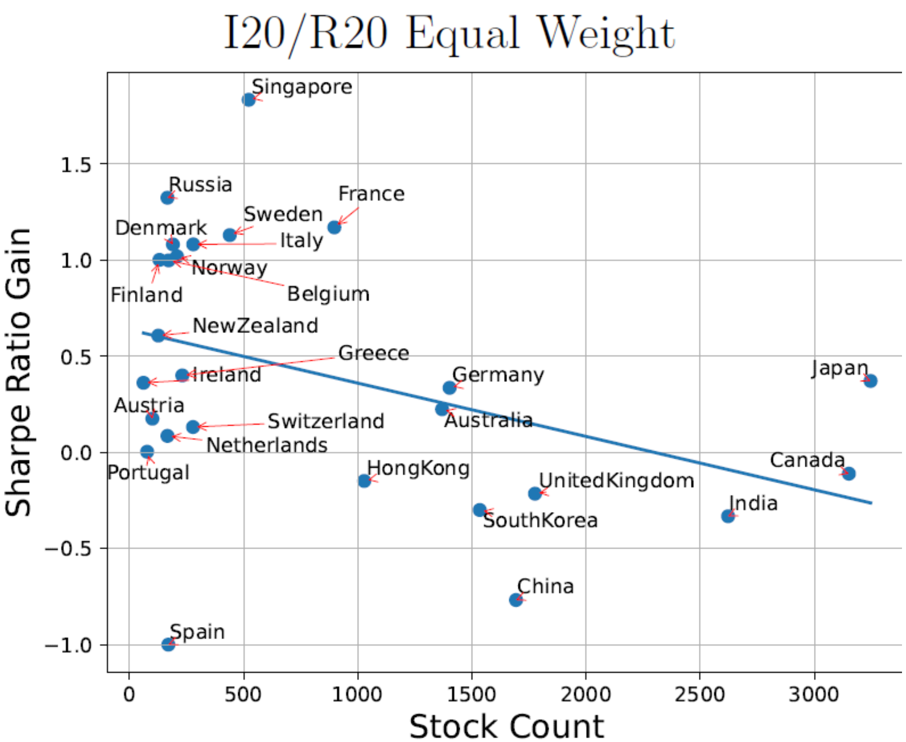
- International Transfer

Table 10: International Transfer and H-L Decile Portfolio Sharpe Ratios (I20/R20)

		Equal Weight			Value Weight		
	Stock Count	Re-train	Direct Transfer	Transfer−Re-train	Re-train	Direct Transfer	Transfer−Re-train
Global	17206	-0.07	0.21	0.29	0.64	-0.25	-0.90
Japan	3056	0.61	0.99	0.37*	0.24	0.12	-0.12
Canada	2924	0.04	-0.07	-0.11	0.52	0.77	0.24
India	1861	0.99	0.66	-0.33	0.94	0.11	-0.83
UnitedKingdom	1783	0.19	-0.03	-0.21	0.66	0.32	-0.34
France	955	-0.36	0.81	1.17***	-0.42	0.30	0.72***
SouthKorea	911	0.89	0.59	-0.30	-0.26	0.75	1.01***
Australia	886	1.97	2.20	0.22	-0.22	0.61	0.83***
Germany	868	-0.26	0.08	0.34*	0.24	0.40	0.16
China	662	0.82	0.06	-0.77	0.39	0.07	-0.33
HongKong	543	1.63	1.48	-0.15	0.51	1.12	0.62***
Singapore	284	0.36	2.20	1.83***	0.24	0.98	0.74***
Sweden	260	0.30	1.43	1.13***	0.61	0.71	0.10
Italy	241	0.63	1.71	1.08***	-0.05	0.65	0.69***

Table 11: International Transfer and H-L Decile Portfolio Sharpe Ratios (I5/R5)

		Equal Weight			Value Weight		
	Stock Count	Re-train	Direct Transfer	Transfer−Re-train	Re-train	Direct Transfer	Transfer−Re-train
Global	17206	0.18	5.20	5.03***	0.46	-3.05	-3.50
Japan	3056	3.56	5.68	2.12***	0.96	1.23	0.27
Canada	2924	9.01	12.12	3.11***	2.98	5.34	2.36***
India	1861	2.52	-1.46	-3.98	0.67	-1.08	-1.75
UnitedKingdom	1783	0.03	-0.23	-0.26	1.04	0.98	-0.06
France	955	2.47	4.09	1.63***	1.12	2.10	0.98***
SouthKorea	911	3.64	1.66	-1.97	1.74	2.39	0.65***
Australia	886	8.28	11.37	3.09***	2.78	3.48	0.70***
Germany	868	-0.29	2.43	2.72***	-0.01	2.93	2.94***
China	662	2.26	-2.19	-4.45	0.66	-0.95	-1.62
HongKong	543	1.97	5.35	3.37***	0.72	2.08	1.36***
Singapore	284	6.98	6.79	-0.20	2.48	3.94	1.46***
Sweden	260	5.43	6.99	1.56***	0.83	2.37	1.54***
Italy	241	2.14	3.55	1.40***	0.76	1.60	0.84***
Switzerland	240	0.48	0.67	0.19	1.30	2.62	1.33***


I20/R20 Equal Weight
Sharpe Ratio Gain
Stock Count
Singapore
Russia
France
Sweden
Denmark
Italy
Norway
Finland
Belgium
NewZealand
Greece
Ireland
Germany
Japan
Austria
Switzerland
Australia
Netherlands
Canada
Portugal
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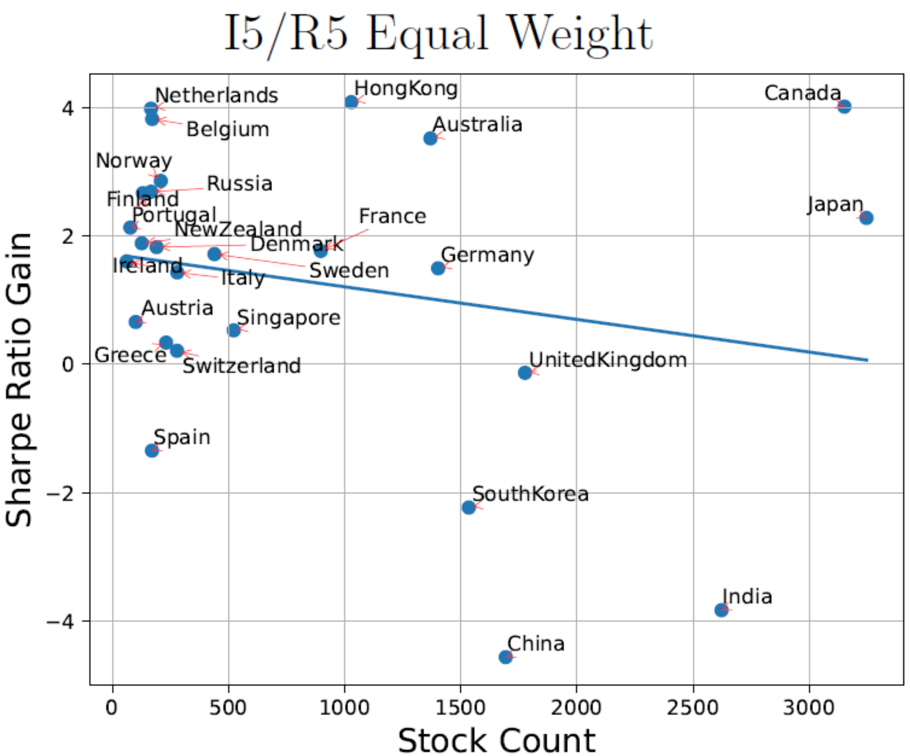
UnitedKingdom
India
SouthKorea
China
Spain

I5/R5 Equal Weight
Sharpe Ratio Gain
Stock Count
Netherlands
HongKong
Canada
Belgium
Australia
Norway
Russia
Finland
Japan
Portugal
France
NewZealand
Denmark
Germany
Ireland
Sweden
Italy
Austria
Singapore
Greece
Switzerland
UnitedKingdom
Spain
SouthKorea
India
China

What dose the CNN learn?

- Association with related predictors

Table 13: CNN Predictions and Standard Stock Characteristics

panel logistic regressions of CNN model forecasts on stock characteristics.

cross-sectional ranks	I5/R20	I20/R20	I60/R20
MOM	-0.05***	0.07***	0.41***
STR	-0.04***	0.42***	0.47***
Lag Weekly Return	-0.77***	-0.80***	-0.48***
Beta	0.12***	0.08***	0.10***
Volatility	-0.08***	-0.22***	-0.29***
52WH	0.04***	0.05***	0.05***
Bid-Ask	0.05***	0.05***	0.20***
Dollar Volume	0.05	-0.15***	-1.86***
Zero Trade	-0.02	0.18***	0.42***
Price Delay	-0.01	-0.02**	-0.01
Size	0.11***	0.59***	0.96***
Illiquidity	-0.25***	-0.35***	-2.10***
McFadden R^2	4.61	7.03	11.92

Table 14: CNN, Future Returns, and Standard Stock Characteristics

	I5/R20			I20/R20			I60/R20		
CNN	0.37***		0.37***	0.54***		0.54***	0.46***		0.45***
MOM		0.17***	0.18***		0.17***	0.16***		0.17***	0.12***
STR		-0.02*	-0.01		-0.02*	-0.05***		-0.02	-0.09***
Lag Weekly Return		-0.19***	-0.07***		-0.19***	-0.05***		-0.19***	-0.13***
Beta		-0.05***	-0.05***		-0.05***	-0.05***		-0.05***	-0.05***
Volatility		-0.09***	-0.09***		-0.09***	-0.06***		-0.09***	-0.05**
52WH		-0.00	-0.01		-0.00	-0.02		-0.01	-0.03**
Bid-Ask		-0.13***	-0.13***		-0.12***	-0.14***		-0.12***	-0.17***
Dollar Volume		-0.08*	-0.09**		-0.08*	-0.09**		-0.08*	0.07*
Zero Trade		-0.02	-0.02		-0.02	-0.05**		-0.02	-0.07***
Price Delay		-0.00	-0.00		-0.00	-0.00		-0.00	-0.01
Size		0.16***	0.17***		0.17***	0.13***		0.17***	0.06
Illiquidity		-0.01	0.01		-0.01	0.02		-0.01	0.14***
McFadden R^2	0.84	0.12	0.93	1.73	0.12	1.79	1.23	0.12	1.30

logistic regressions of future stock returns on image-based forecasts while simultaneously controlling for the other characteristics.

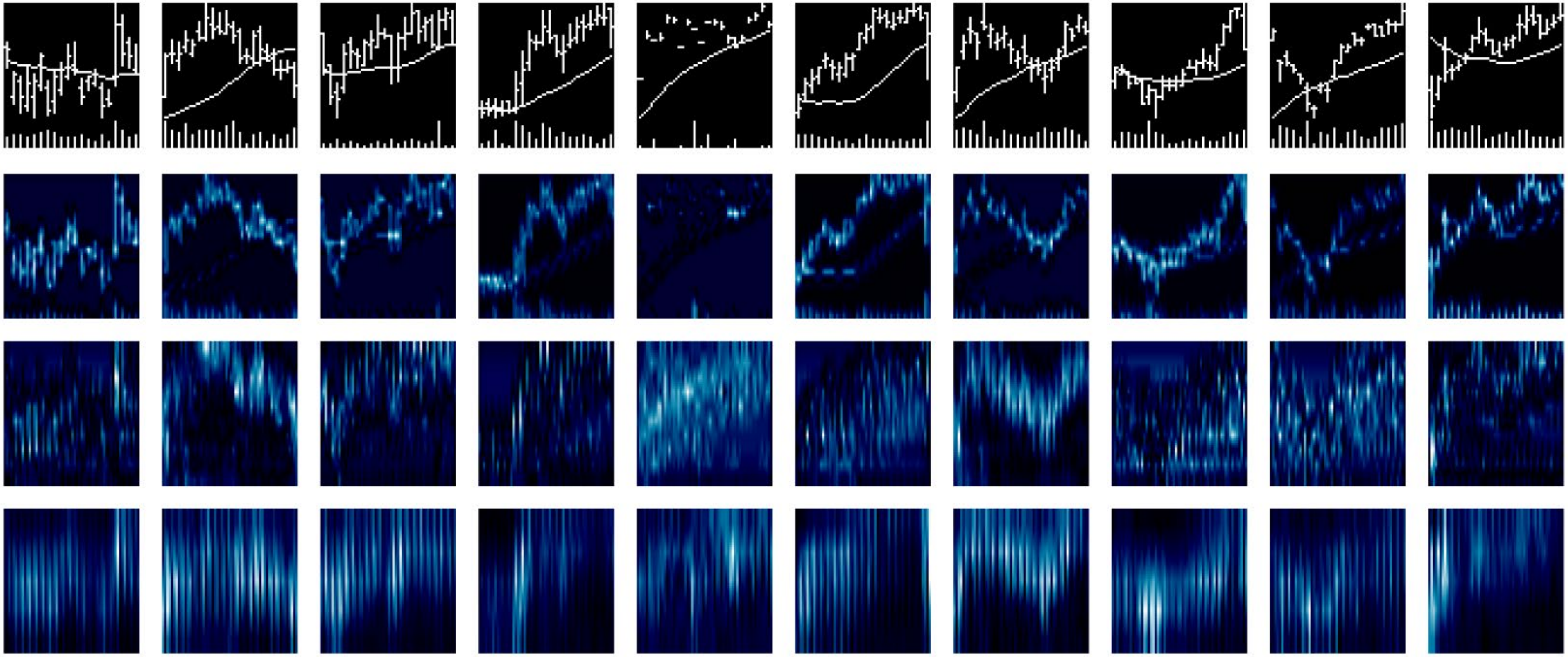
- Image-Based linear approximation

Table 15: Linear Regressions Using Market Data With Image Scaling

	CNN as Dep. Var.			Positive Return Indicator as Dep. Var.								
	5D5P	5D20P	5D60P	5D5P			5D20P			5D60P		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CNN				4.07*		4.28*	5.09*		6.27	6.07*		7.63*
open lag 1	-0.57*	0.01	0.29*		-0.23	-0.03		-0.07	-0.02		0.01	-0.07
open lag 2	0.27*	0.55*	0.22*		0.08	0.04*		0.12	0.02		0.05	-0.00
open lag 3	0.16*	-0.29*	-0.09*		0.05	0.01		-0.02	0.01		-0.13	-0.04
open lag 4	0.04*	-0.13*	-0.06*		0.02	0.00		-0.03	-0.00		-0.04	-0.01
open lag 5	0.10*	0.21*	0.45*		0.03	0.01		0.02	0.04		-0.04	-0.03
high lag 1	2.64*	0.99*	1.07*		0.61	0.11*		0.36	0.12		0.39*	-0.06
high lag 2	-0.27*	0.47*	0.77*		-0.07	-0.06		0.07	-0.05		0.13*	-0.18
high lag 3	-0.43*	-0.18*	-0.20*		-0.06	0.03*		-0.01	-0.00		0.07	0.05
high lag 4	-0.47*	-0.14*	-0.22*		-0.04	0.05*		0.04	0.02		0.03	0.05
high lag 5	-0.13*	0.31*	-0.38*		-0.05	0.01		0.09	0.02		0.03	-0.05
McFadden R^2	35.29	33.32	21.96	1.35	0.99	1.38	0.94	0.58	0.99	1.56	0.50	1.69

- the most important explanatory variables for the CNN forecast are the first lags of closing, high, and low prices
- more than half of the variation in image-based predictions is attributable to non-linear functions of the underlying market data.

- Visualizing the model



(a) Images Receiving "Up" Classification

Conclusion

- The CNN constructs image-based forecasts that in general outperform traditional price trend signals
- CNN's transferability to other time scales and international markets is robust

- Data
  - CRSP, price and trading volume data
  - Transform data into images
- Method
  - CNN model
- Findings:
  - Image-based CNN predictions are powerful and robust predictors of future returns.
  - Short-horizon predictability can translate into long range predictability via transfer learning → other market and time scales