INVEST: An Intelligent System for Automated Share Evaluation using Semantic Bayesian Networks

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ABSTRACT

Portfolio management is a phased decision-making process used by investors to build a profitable portfolio of financial securities. The initial share evaluation phase involves identifying suitable securities for investment, achieved through manual evaluation of multiple erratic factors. Semantic Bayesian networks (SBNs) are a class of Artificial Intelligence techniques that support explainability in intelligent systems. Drake proposed *INVEST*, an intelligent decision support system framework for share evaluation using SBNs. This research empirically evaluates the system and several extensions under various conditions for Johannesburg Stock Exchange-listed share evaluation. The results demonstrate that the base system consistently outperforms the benchmark, however, portfolio performance degrades for higher β values. Furthermore, the base system is unstable and susceptible to noisy data. The results further provide evidence in support of extending the *INVEST* framework and validate the integration of a graph neural network predictive component for short-term holding periods.

CCS CONCEPTS

• **Computing methodologies** → **Probabilistic reasoning**.

KEYWORDS

share evaluation, portfolio management, JSE, semantic bayesian networks

1 INTRODUCTION

Portfolio management is a complex decision-making process that aims to maximise return [10] through the proportional allocation of investable capital into identified financial securities. The initial share evaluation phase involves identifying securities with suitable characteristics for inclusion in a portfolio. Portfolio selection is the successive phase of portfolio management and determines the optimal allocation of the set of identified shares in a portfolio [4]. The stock market is a dynamic, non-linear and chaotic system. This requires investment professionals to assess and evaluate multiple factors, including contradictory information when deciding whether a share is suitable for inclusion in an investment portfolio [3]. Intelligent systems incorporate Artificial Intelligence (AI) techniques to automate tasks and support human decision-making. The *INVEST* system, proposed by Drake [3], is one such intelligence system that incorporates ontologies and Bayesian networks to support decision-making for share evaluation on the Johannesburg Stock Exchange (JSE). Ontologies are used to formally encode unstructured expert information into a representative, machine-understandable form [9], whilst Bayesian networks (BNs) are useful in the financial domain as it represents uncertain, ambiguous or incomplete knowledge. Furthermore, BNs have the ability to convey how an investment decision is reached [2]. This characteristic can be classified as a glass-box approach; it allows users to understand automated decisions by explaining predictions [8]. In this research, we will empirically evaluate the *INVEST* system with varying conditions and test several system extensions. Firstly, we will evaluate the base *INVEST* system as designed by Drake [3]. Secondly, we will conduct an ablation study to assess the relative importance of each component in the overall framework. Thirdly, we will extend the system to include systematic risk within the BN topology. Fourthly, we will test the stability and robustness of the *INVEST* system through a noise simulation component. Finally, we will integrate a deep learning predictive component into the *INVEST* system.

2 BACKGROUND AND RELATED WORK

Ontologies are used to encapsulate background domain knowledge in a machine understandable form [9]. BNs are graphical, decision modelling tools [2] that encodes a representation of probabilistic knowledge within a domain [5]. Furthermore, BNs provide a mechanism to deal with the inherent uncertainty in many domains. It is modelled as a Direct Acyclic Graph (DAG), with causal links (arcs) between variables (nodes). Each non-root node has a conditional probability table associated with it. This is quantified using Bayes's formula to obtain conditional probabilities. Furthermore, decision networks are BNs extended with utility functions and variables representing decisions [3]. Utility nodes maximise their value by obtaining the best decision rule for each decision node [3].

Semantic Bayesian networks are BNs enriched with knowledge, often represented in an ontology, and are an explainable AI technique. Semantic Bayesian networks have been incorporated into intelligent decision support systems (IDSS) to solve domain-specific problems [1] [3]. However, the application of Semantic BNs to share evaluation and portfolio management is not widely explored in the literature.

Drake [3] designed *INVEST*, a novel IDSS framework using ontologies and BNs for evaluating Johannesburg Stock Exchange (JSE)-listed shares. Specifically, *INVEST* uses three decision networks to flexibly support medium-term realistic share evaluation decisions for investment professionals, while overcoming limitations on transparency and explainability inherent in investment decisions [2]. However, the framework was theoretically evaluated and no experimental results were obtained in the study.

3 DESIGN AND IMPLEMENTATION

3.1 Architecture

3.1.1 System Design. The system is composed of six submodules within the *INVEST* module. The package diagram (Figure 1) depicts the dependencies between modules.

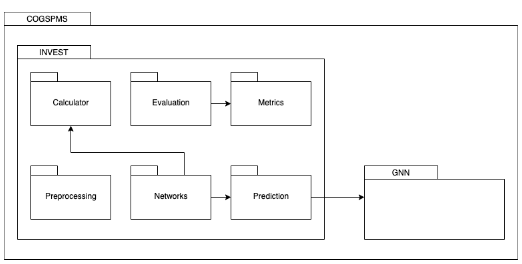

Figure 1: *INVEST* Package Diagram

- *INVEST*: This module contains a `Store` class, which represents the central point of the system. Responsibilities include invoking the functionality of the 6 submodules and running different experiments dependent on user input. The core functionality contained in this module map to the `Rules Manager`, `Explanation Facility` and `User Interface` components from the *INVEST* system design [3].
- *Preprocessing*: This submodule contains data loading and preprocessing utilities, performing the functions of the `Financial Data Reader` and `Database` in the *INVEST* system [3]. Furthermore, this component has been extended to include a noise simulation component to facilitate system stress tests.
- *Calculator*: This submodule performs the financial calculations of the system for each company, using financial ratios computation and thresholding logic. Financial ratios produce a numerical output, which the threshold component subsequently converts to discrete states required as input for the BNs. This component maps to the `Financial Calculator` component in the *INVEST* system [3]. Furthermore, this component performs the functionality of the `Temporary Storage Space` component in the *INVEST* system [3], as separate intermediate storage was not required.
- *Networks*: This submodule contains the implementation of three decision networks used to reach an investment decision: Value Evaluation, Quality Evaluation, and Investment Recommendation. These BNs conduct inference using the evidence returned by the thresholding component. This component maps to the `Bayesian Network` component in the *INVEST* system [3].
- *Evaluation*: The *INVEST* system is evaluated through back-testing using historical data for shares listed on the JSE. This submodule contains the validation procedures and depends on a Metrics submodule that houses risk and risk-adjusted return metrics. This component is an addition to the *INVEST* system design, as evaluation is not explicitly included in the original design.
- *Metrics*: This submodule contains the logic to determine portfolio performance, which is calculated using risk and risk-adjusted return metrics. This component is an addition to the *INVEST* system design, and therefore does not map to any component in the *INVEST* system.
- *Prediction*: This component includes logic to facilitate the integration of a Graph Neural Network (GNN) with the BNs. Prediction is performed based on the close price data of each share. This component is an addition to the *INVEST* system design, as it is a novel integration explored in this research.

3.1.2 Implementation. Python, a general-purpose programming language is the selected development platform for the system. The `PyAgrum` library is used to create and manage Bayesian networks, given its ability to perform efficient computations. Furthermore, a visualization web console was developed using a *Flask* server and *React*. This provides the user an opportunity to select different experiments, and obtain a graphical view of the results in comparison to the relative benchmark.

3.1.3 Ontology Design. The *INVEST* ontology supplies investment professionals with a clear structure of useful information and articulates concepts and properties, which are required by the BN as evidence. The BN construction is informed by the *INVEST* ontology, where factors of the ontology map to variables in the BN, and instances of these factors will map to states for the relevant factors. The `Factor` class is constructed hierarchically with three sub-classes to represent sub-categories. The abstract `Factor` class contains four abstract classes relating to evaluation objectives. The second level represents Factor Type, while the lower level classes represent concrete observable factors. The ontology remained unchanged for experiments excluding the systematic risk extension.

3.1.4 Bayesian Networks. The BNs support investment professionals in their investment decisions. The *INVEST* system has three decision networks, which correspond to the three sequential steps in the decision-making process: Value Evaluation, Quality Evaluation, and Investment Recommendation.

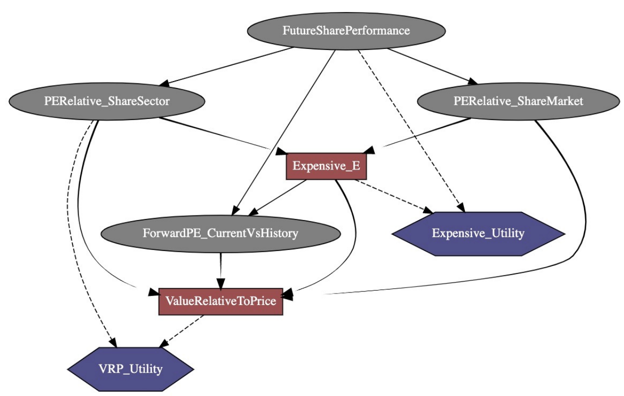

Figure 2: *INVEST* Value Evaluation Bayesian Network

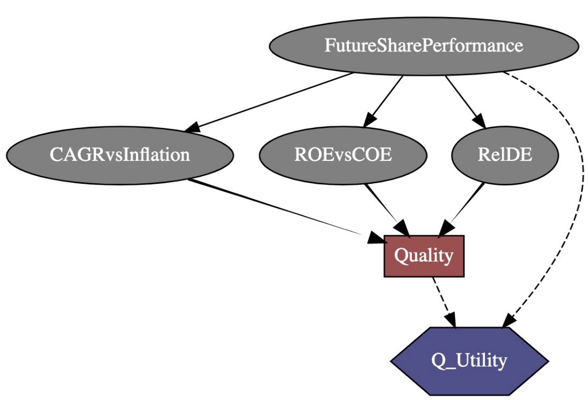

Figure 3: *INVEST* Quality Evaluation Bayesian Network

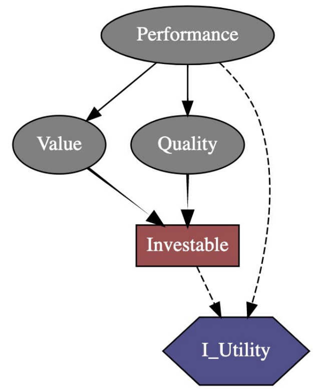

Figure 4: *INVEST* Investment Recommendation Bayesian Network

The Value Evaluation network (Figure 2) is used to evaluate a share relative to price and determines whether a share is `Cheap`, `FairValue` or `Expensive`. The Quality Evaluation network (Figure 3) is used to evaluate the quality of a share and determines whether a share is of a `Low`, `Medium` or `High` quality. Finally, The Investment Recommendation network (Figure 4) incorporates the output of the Quality and Value BNs to reflect the decision process performed by investors: evaluating whether the price of a share is reasonable and the quality of the share, thus providing an investment recommendation for a specific share. This network produces a final `Yes` or `No` decision pertaining to system's assessment of the share's suitability for investment. Each BN contains chance nodes (oval-shaped), decision nodes (rectangular shaped) and utility nodes (hexagonal shaped). Chance nodes represent the factors used to evaluate the shares as evidence in a probabilistic form. Each chance node has its own conditional probability table (CPT), which was specified by Drake [3]. Specified expert utilities were assigned to utility nodes [3]. The FutureSharePerformance node, present in all decision networks, uses historical data to reflect the level of accuracy of factors used in predicting future share performance.

3.2 Experimental Design

3.2.1 Data. The dataset used (Table 1) consists of price and fundamental data for 36 shares listed on the JSE between 2012 - 2018: 17 shares from the General Industrials sector and 19 shares from the Consumer Services sector [3]. This dataset is selected to support accurate comparative evaluation and reproducibility of results. For the addition of noise, a fractional sample of the dataset is randomly adjusted positively or negatively by the standard deviation of the variable of interest.

Table 1: INVEST dataset between 2012-2018

Feature	Frequency
Date	Daily
Company Name	–
Beta Leveraged	Monthly
Share Beta	Daily
Close Price	Daily
Price Earnings	Yearly
Debt/Equity Industry	Yearly
Inflation Rate	Yearly
Market Rate of Return	Yearly
Risk-Free Rate of Return	Yearly
Price Earnings Market	Yearly
Price Earnings Sector	Yearly
Earning Per Share	Yearly
Return on Equity	Yearly
Debt/Equity	Yearly
Shareholders Equity	Yearly

3.2.2 Benchmark. The JSE All-Share Index, General Industrials (JGIND) and Consumer Services (JCSEV) are the selected benchmark indices to validate the share evaluation recommendations for the respective sectors. The benchmark dataset includes FTSE/JSE General Industrials index data, FTSE/JSE Consumer Services index data, as well as the FTSE/JSE All Share index data.

3.2.3 Setup. Each experiment is conducted on an Apple MacBook Pro with an Intel(R) Core(TM) i5 CPU @ 2.4 GHz. Each experiment was run with the default margin of safety (threshold) of 0.1 and a β of 0.2 if not specified otherwise.

3.2.4 Evaluation. Return and Risk-Adjusted Return metrics are used to evaluate the performance of the semantic BNs for share evaluation. These metrics include Annual Return (AR), Compound Return (CR), Average Annual Return (AAR), Treynor Ratio (TR) and Sharpe Ratio (SR). This selection is informed by our requirements of reproducibility [3] and to support robust evaluation of other BN topologies. The system is evaluated over one-year [3] and one-month holding periods.

$$AR = \frac{Portfolio\ Value_{Year+1}}{Portfolio\ Value_{Year}} - 1 \tag{1}$$

$$CR = \left(\frac{Portfolio\ Value_{Year+N}}{Portfolio\ Value_{Year}}\right)^{\frac{1}{N}} - 1 \tag{2}$$

$$AAR = \frac{\frac{Portfolio\ Value_{Year+N}}{Portfolio\ Value_{Year}}}{N} \tag{3}$$

$$TR = \frac{r_p - r_f}{\beta_p} \tag{4}$$

$$SR = \frac{r_p - r_f}{\sigma_p} \tag{5}$$

4 RESULTS

4.1 Base INVEST

4.1.1 Experimental Configuration. The experiment is conducted to validate the *INVEST* system results [3]. This experiment was run with $\beta = \{0.2, 0.6, 1.0, 1.4, 1.6\}$ for years 2015 to 2018 and compared to the benchmarks for the respective sectors.

4.1.2 Results. Figure 5 illustrates the annual returns of the *INVEST* system for General Industrials and the Consumer Services sector. Although the resultant investment portfolio included a slightly different set of shares to the theoretical results, the experimental results demonstrate that the annual returns significantly outperformed the General Industrials benchmark in 2016 and the Consumer Services benchmark in 2015 and 2016 respectively.

Table 2 measures portfolio performance for the INVEST-recommended portfolio with a $\beta = 0.2$. CR, AAR, Treynor and Sharpe ratio measures for the INVEST-recommended Consumer Services portfolio outperformed the corresponding benchmark metrics. While CR, AAR and Treynor ratio outperformed the corresponding benchmark metrics for the INVEST-recommended General Industrials portfolio, we observe that the Sharpe ratio was slightly outperformed by the benchmark.

We note that when the baseline experiment is conducted with $\beta = 0.6$ (Figure 6), the portfolio performance results in Table 3 show that only the Consumer Services portfolio was able to outperform the index consistently. The results for General Industrials degrade for the higher β value. Furthermore, we note that when the experiment is conducted with $\beta \geq 1$ (Figure 7), the results obtained are identical, given that an identical portfolio of shares is selected. Table 4 illustrates that the performance of the Consumer Services recommended portfolio outperforms the benchmark consistently, whilst the same does not hold true for General Industrials. Lastly, we note that in 2016, General Industrials and Consumer Services obtained returns in excess of the benchmark for $\beta = \{0.2, 0.6, 1.0\}$.

4.2 Ablation Study

4.2.1 Experimental Configuration. The ablation study entailed running the Value BN and Quality BN independently. The experiment was conducted with $\beta = \{0.2, 1.0\}$ for years 2015 to 2018, and the results were compared to the base *INVEST* system.

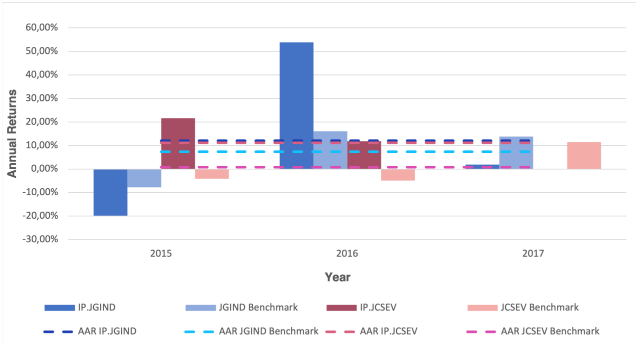

Figure 5: Annual Returns of *INVEST* vs Benchmark for 2015 - 2018 ($\beta = 0.2$)

Table 2: Performance comparison of *INVEST* investment portfolio and benchmark for 2015 - 2018 ($\beta = 0.2$)

Measure	IP.JGIND	JGIND	IP.JCSEV	JCSEV
CR	**13.33%**	6.96%	**37.55%**	0.51%
AAR	**12.01%**	7.32%	**11.13%**	0.83%
TR	**0.37**	0.09	**0.82**	0.01
SR	0.25	**0.35**	**2.58**	0.03

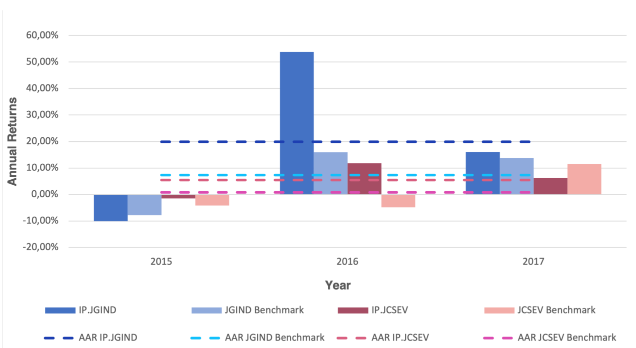

Figure 6: Annual Returns of *INVEST* vs Benchmark for 2015 - 2018 ($\beta = 0.6$)

Table 3: Performance comparison of *INVEST* investment portfolio and benchmark for 2015 - 2018 ($\beta = 0.6$)

Measure	IP.JGIND	JGIND	IP.JCSEV	JCSEV
CR	6.86%	**6.96%**	**14.30%**	0.51%
AAR	**19.94%**	7.32%	**5.52%**	0.83%
TR	**0.25**	0.09	**0.4**	0.01
SR	0.15	**0.35**	**1.42**	0.03

Figure 7: Annual Returns of *INVEST* vs Benchmark for 2015 - 2018 ($\beta \geq 1$)

Table 4: Performance comparison of *INVEST* investment portfolio and benchmark for 2015 - 2018 ($\beta \geq 1$))

Measure	IP.JGIND	JGIND	IP.JCSEV	JCSEV
CR	2.53%	**6.96%**	**9.49%**	0.51%
AAR	**20.80%**	7.32%	**6.33%**	0.83%
TR	**0.1**	0.09	**0.25**	0.01
SR	0.06	**0.35**	**0.5**	0.03

4.2.2 Results. This experiment yielded unexpected results for $\beta = 0.2$. Considering only the Value BN (Table 5 and Figure 8), we observe that the resultant investment portfolio outperformed the *INVEST* baseline results across all metrics for Consumer Services, and over all metrics for General Industrials excluding AAR, given the lower annual returns in both 2015 and 2016. We observe a significant decrease in performance when $\beta = 1$ (Figure 9 and Table 6). Excluding the Value BN and testing only the Quality BN for $\beta = \{0.2, 1.0\}$ resulted in a stark decrease in performance (Figure 10 , Table 7, Figure 11 and Table 8). In both configurations, the base *INVEST* system outperformed the recommended investment portfolio.

Table 5: Performance comparison of Value Evaluation network investment portfolio and *INVEST* for 2015 - 2018 ($\beta = 0.2$)

Measure	IP.JGIND.V	IP.JGIND	IP.JCSEV.V	IP.JCSEV
CR	**16.05%**	13.33%	**43.19%**	37.55%
AAR	5.13%	**12.01%**	**11.61%**	11.13%
TR	**0.5**	0.37	**0.97**	0.82
SR	**0.33**	0.25	**2.95**	2.58

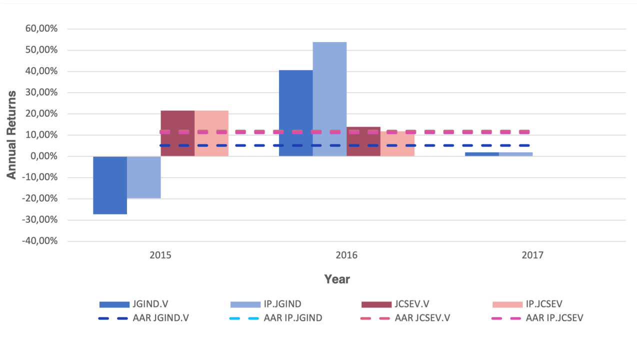

Figure 8: Annual Returns of Value Evaluation network vs *INVEST* for 2015 - 2018 ($\beta = 0.2$)

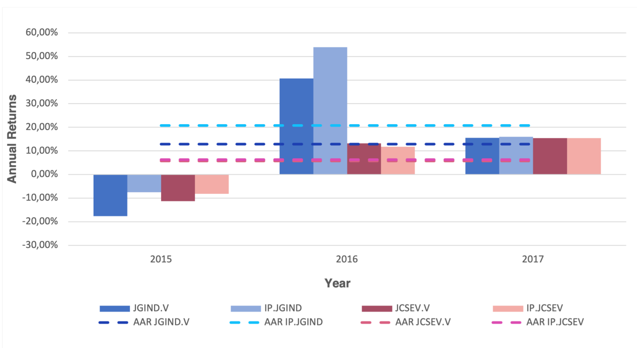

Figure 9: Annual Returns of Value Evaluation network vs *INVEST* for 2015 - 2018 ($\beta = 1$)

Table 6: Performance comparison of Value Evaluation network investment portfolio and *INVEST* for 2015 - 2018 ($\beta = 1$)

Measure	IP.JGIND.V	IP.JGIND	IP.JCSEV.V	IP.JCSEV
CR	-0.61	**2.53%**	7.69	**9.49%**
AAR	12.84	**20.80%**	5.78%	**6.33%**
TR	-0.03	**0.1**	0.21	**0.25**
SR	-0.02	**0.06**	0.35	**0.5**

4.3 Extended INVEST

4.3.1 Ontology Design. To effectively extend the *INVEST* Bayesian Network, the *INVEST* ontology required an extension. The extension requires systematic risk to be modelled within the system, therefore, the BN topology requires the *INVEST* ontology `Factor` class to be extended. The `QualityFactor` abstract class (top-level) is modified through the addition of systematic risk as a factor type (second-level) and the β coefficient as a concrete observable factor (lower-level).

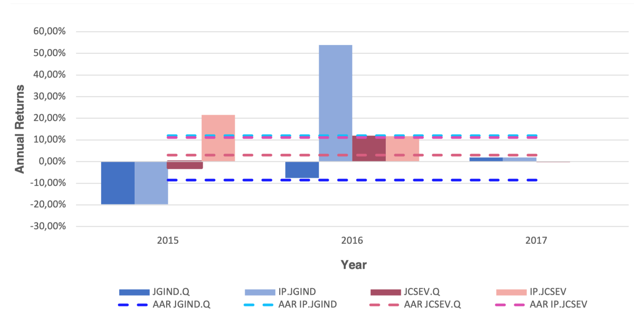

Figure 10: Annual Returns of Quality Evaluation network vs *INVEST* for 2015 - 2018 ($\beta = 0.2$)

Table 7: Performance comparison of Quality Evaluation network investment portfolio and *INVEST* for 2015 - 2018 ($\beta = 0.2$)

Measure	IP.JGIND.Q	IP.JGIND	IP.JCSEV.Q	IP.JCSEV
CR	-53.24%	**13.33%**	19.80%	**37.55%**
AAR	-8.48%	**12.01%**	2.95%	**11.13%**
TR	-1.45	**0.37**	0.49	**0.82**
SR	-3.29	**0.25**	1.7	**2.58**

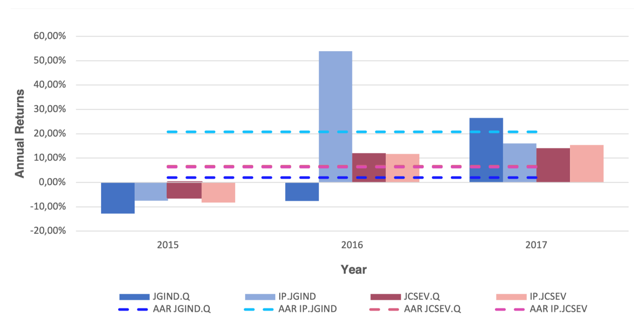

Figure 11: Annual Returns of Quality Evaluation network vs *INVEST* for 2015 - 2018 ($\beta = 1$)

Table 8: Performance comparison of Quality Evaluation network investment portfolio and *INVEST* for 2015 - 2018 ($\beta = 1$)

Measure	IP.JGIND.Q	IP.JGIND	IP.JCSEV.Q	IP.JCSEV
CR	1.47	**2.53%**	5.52%	**9.49%**
AAR	2.02%	**20.80%**	**6.70%**	6.33%
TR	0.05	**0.1**	0.17	**0.25**
SR	-0.04	**0.06**	0.33	**0.5**

The Protégé-OWL tool is used to modify the relevant ontology sub-classes. This tool produces an XML encoding of the ontology represented in OWL.

4.3.2 Network Design. Figure 12 depicts the systematic risk extension, which was included by modifying the topology of the Quality Evaluation BN to model risk within the system.

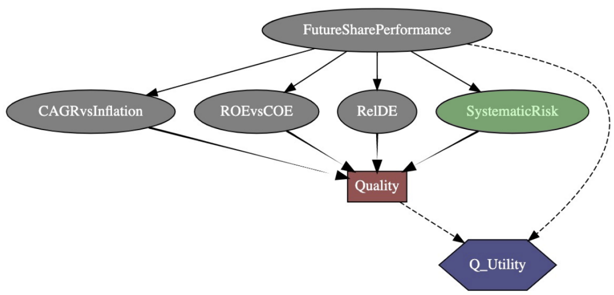

Figure 12: *INVEST* Extended Quality Evaluation Bayesian Network

4.3.3 Experimental Configuration. This experiment was conducted for $\beta = \{0.2, 1.0\}$ for years 2015 to 2018, and was compared to the base *INVEST* system.

4.3.4 Results. From Figure 13 and Table 9, we note that the extended system outperformed the baseline results for General Industrials, however, this was not the case for Consumer Services although the extension yielded marginally improved performance as measured by AAR. For $\beta = 1$ (Figure 14 and Table 10), performance degraded for General Industrials, however, near parity was achieved relative to the base system. Furthermore, we note that the results did not improve for Consumer Services. We note the positive performance of the annual returns for General Industrials and Consumer Services INVEST-recommended portfolios in 2016.

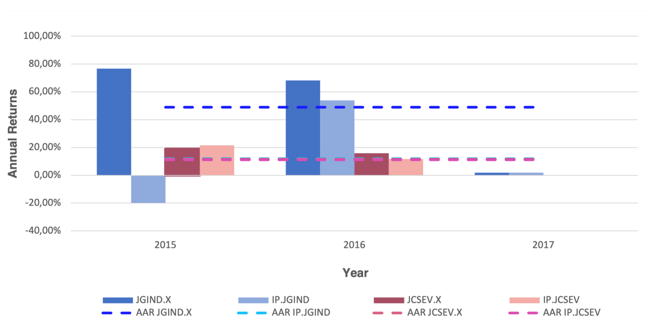

Figure 13: Annual Returns of *INVEST* + Systematic Risk vs *INVEST* for 2015-2018 ($\beta = 0.2$)

4.4 Noisy Data

4.4.1 Experimental Configuration. A noise simulation component was introduced to test the stability and robustness of the *INVEST* system. This simulates the inherent noise exhibited in complex systems such as the stock market. For each simulation, a varying fraction (5%, 10%, & 15%) of the fundamental factors in the dataset are noised. The experiment was conducted over 10 runs. The results obtained for each fraction of noise (Figure 15) records the mean metric values over the 10 runs.

4.4.2 Results. Figure 15 illustrates that as the percentage of noise increases, the General Industrials investment portfolio decreases in performance and does not obtain results equivalent to the base system. Remarkably, we find that all Consumer Service's portfolio measures decline at the 5% degree of noise, and increase thereafter. However, the baseline is only substantially outperformed for CR and Treynor ratio as the level of noise approaches 15%. We therefore observe inherent instability in the system.

Table 9: Performance comparison of *INVEST* + Systematic Risk and *INVEST* for 2015 - 2018 ($\beta = 0.2$)

Measure	IP.JGIND.X	IP.JGIND	IP.JCSEV.X	IP.JCSEV
CR	**73.64%**	13.33%	32.71%	**37.55%**
AAR	**48.92%**	12.01%	**11.63%**	11.13%
TR	**2.49**	0.37	0.79	**0.82**
SR	**1.29**	0.25	2.38	**2.58**

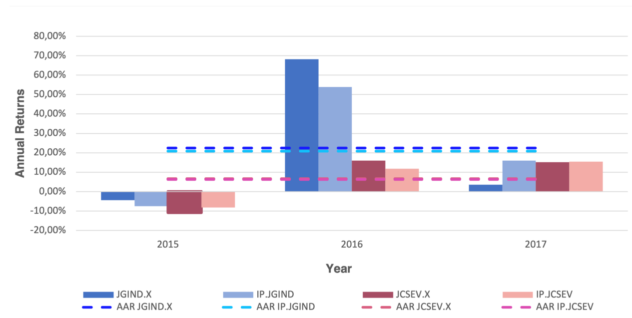

Figure 14: Annual Returns of *INVEST* + Systematic Risk vs *INVEST* for 2015 - 2018 ($\beta = 1$)

Table 10: Performance comparison of *INVEST* + Systematic Risk and *INVEST* for 2015 - 2018 ($\beta = 1$)

Measure	IP.JGIND.X	IP.JGIND	IP.JCSEV.X	IP.JCSEV
CR	2.50%	**2.53%**	6.30%	**9.49%**
AAR	**22.43%**	20.80%	**6.73%**	6.33%
TR	**0.13**	0.10	0.20	**0.25**
SR	0.04	**0.06**	0.28	**0.5**

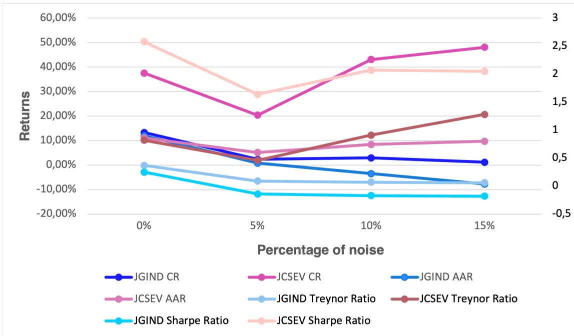

Figure 15: Noise simulation for 2015 - 2018 ($\beta = 0.2$)

4.5 Hybrid Integration

4.5.1 Experimental Configuration. A hybrid experiment was performed by integrating a graph neural network [7] model as a deep learning predictive component into the system. To perform the hybrid experiment, the FutureSharePerformance node was classified as "Positive", "Negative" or "Stagnant" [3] using inference from the GNN model. Evidence is added to FutureSharePerformance node in the Value Network based on the mean predicted price as a proxy to reflect the accuracy of factors in predicting future share performance [3]. The procedure of adding evidence to the remaining nodes in the network remain unchanged.

The continuous output of the GNN model is converted into a discrete value using the following piece-wise function, where $\hat{y_{i+1}}$ and y_i are the predicted future and current price.

$$x = \begin{cases} 1 & \frac{\hat{y_{i+1}}}{y_i} \geq 1.01 \\ 0 & 0.99 < \frac{\hat{y_{i+1}}}{y_i} < 1.01 \\ -1 & \frac{\hat{y_{i+1}}}{y_i} \leq 0.99 \end{cases} \tag{6}$$

If the mean predicted price is greater than 2% of the current price for a particular year, share performance is classified as Positive. If it is less than 2%, the classification is Negative, else the performance is deemed Stagnant.

The experiment was conducted for $\beta = \{0.2, 1\}$ for one-year and one-month holding periods and compared to the baseline *INVEST* system results. The experiment was run for years 2015 - 2018.

4.5.2 Results. Table 11 and Table 12 illustrates that identical results were produced, given that the identical set of shares was selected for $\beta = 0.2$. However, when $\beta = 1$ for a one-year holding period (Figure 16 and Table 13), the results demonstrate no performance improvement for Consumer Services in comparison to the baseline *INVEST* system results. We note that for the General Industrials sector, the hybrid system outperforms the baseline results measured across all metrics.

Table 11: Performance comparison of *INVEST* + GNN and *INVEST* for 2015 - 2018 over a one-year holding period ($\beta = 0.2$)

Measure	IP.JGIND.G	IP.JGIND	IP.JCSEV.G	IP.JCSEV
CR	13.33%	13.33%	37.55%	37.55%
AAR	12.01%	12.01%	11.13%	11.13%
TR	0.37	0.37	0.82	0.82
SR	0.25	0.25	2.58	2.58

Table 12: Performance comparison of *INVEST* + GNN and *INVEST* for 2015 - 2018 over one-month holding period ($\beta = 0.2$)

Measure	IP.JGIND.G	IP.JGIND	IP.JCSEV.G	IP.JCSEV
CR	-1.13%	-1.13%	0.31%	0.31%
AAR	5.30%	5.30%	2.61%	2.61%
TR	-0.03	-0.03	0	0
SR	-0.06	-0.06	0.03	0.03

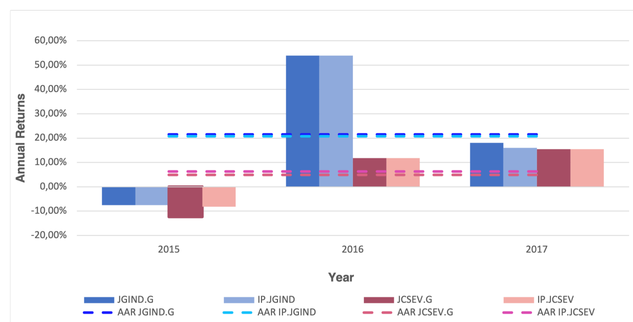

Figure 16: Annual Returns of *INVEST* + GNN and *INVEST* for 2015 - 2018 over a one-year holding period ($\beta = 1$)

Table 13: Performance comparison of *INVEST* + GNN and *INVEST* over a one-year holding period ($\beta = 1$)

Measure	IP.JGIND.G	IP.JGIND	IP.JCSEV.G	IP.JCSEV
CR	**3.75%**	2.53%	6.82%	**9.49%**
AAR	**21.49%**	20.80%	4.94%	**6.33%**
TR	**0.13**	0.10	0.18	**0.25**
SR	**0.09**	0.06	0.30	**0.5**

When $\beta = 1$ for the one-month holding period, we see an improvement in performance (Figure 17 and Table 14). The General Industrials portfolio completely outperform the corresponding portfolio recommended by the baseline *INVEST* system. However, although this is not the case for Consumer Services, the results demonstrate a drastic improvement relative to the one-year holding period. The results produced are near parity to those produced by the baseline *INVEST* system.

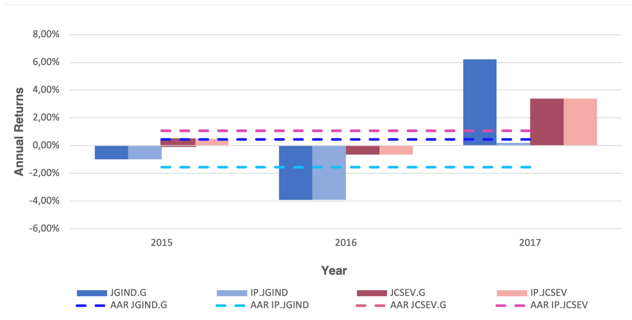

Figure 17: Annual Returns of *INVEST* + GNN and *INVEST* for 2015 - 2018 over a one-month holding period (β = 1)

Table 14: Performance comparison of *INVEST* + GNN and *INVEST* for 2015 -2018 over a one-month holding period (β = 1)

Measure	IP.JGIND.G	IP.JGIND	IP.JCSEV.G	IP.JCSEV
CR	**0.79%**	-0.48%	1.29%	**1.48%**
AAR	**0.44%**	-1.56%	1.07%	**1.08%**
TR	**0.02**	-0.01	0.02	**0.03**
SR	**0.09**	-0.18	0.34	**0.40**

5 DISCUSSION AND CONCLUSIONS

This research has empirically evaluated an implementation of the *INVEST* framework for share evaluation on the JSE. Our results illustrate that the β parameter has had a considerable impact on the performance of the recommended investment portfolio. β is included as a preference factor: a preselected manual parameter that represents an investor's risk appetite. It is used to eliminate shares that do not meet an investor's specified investment criteria, rather than considering systematic risk in a network and therefore speaks less to the system and more to the investment strategy. As β increased from 0.2 to $\beta \geq 1$ for the base experiment, the performance of the investment portfolio degraded, specifically for the General Industrials sector. However, we note that it was still able to outperform the benchmark in the majority of the conducted experiments. This provides cautionary preliminary evidence towards supporting a more conservative investment approach where the share has less systematic risk in relation to the market. With the inclusion of systematic risk in the quality network, we note that with a lower β value the system produced improved results. However, as β increased to 1, it had a marginal impact on results. Therefore, we conclude that there is tentative evidence to include systematic risk in the network. Furthermore, the results in Figure 15 demonstrate that the *INVEST* system cannot entirely withstand noise given that different results are produced in comparison to the baseline. We, therefore, conclude that the system is not entirely stable and robust.

Unexpectedly, the Value network in the ablation study has shown to improve results relative to the base *INVEST* system with a β value of 0.2, although as β increased to 1, performance degraded providing additional preliminary evidence in support of a conservative investment strategies. Although an improvement was achieved with the Value network, the quality network severely underperformed the base *INVEST* system for β = 0.2 and β =1. Thus, we can conclude that the Value network is an imperative component of the *INVEST* system in comparison to the quality network. Given this, the decision node's utility could be modulated in the Invest Recommendation network to reflect its relative influence within the overall framework. The *INVEST* system is focused on prediction under the value investing approach: investing in stocks that are trading at a value less than their intrinsic value, given that in the future, they will yield abnormal returns through the price reversals [6]. Based on this approach, this finding demonstrates that solely finding quality shares without consideration of price produces diminishing returns and degrades performance of the *INVEST* system.

The results demonstrated that the base *INVEST* system, *INVEST*+Systematic risk and Value BN were able to outperform the benchmark and baseline results for both indexes for all β values in 2016.

The results of the GNN integration displayed a slight improvement in results for the General Industrials sector for a one-year holding period, however, the Consumer Services severely underperformed the base system. We posit that the results are a consequence of the specified prediction window. The GNN model outputs predicted values for the next 10 days, while the investment portfolio holding period is one year. However, we observe improved performance when the holding period was reduced to one month. Specifically, General Industrials outperformed the base system, while an improvement in the Consumer Services sector is demonstrated and near parity is achieved. We conclude that a GNN, or more broadly, Machine Learning model integration is valuable for short-term holding periods, such that the period is more consistent with the prediction horizon of the model.

Based on our empirical evaluation of *INVEST*, we conclude that the *INVEST* system demonstrates consistent excess returns for majority of the General Industrials and Consumers

Table 15: Performance comparison of JGIND Experiments for 2015 - 2018 $\beta = 0.2$)

Measure	IP.JGIND	IP.JGIND.V	IP.JGIND.Q	IP.JGIND.X	IP.JGIND.G
CR	13.33%	16.05%	-53.24%	**73.64%**	13.33%
AAR	12.01%	5.13%	-8.48%	**48.92%**	12.01%
TR	0.37	0.5	-1.45	**2.49**	0.37
SR	0.25	0.33	-3.29	**1.29**	0.25

Table 16: Performance comparison of JCSEV Experiments for 2015 - 2018 ($\beta = 0.2$)

Measure	IP.JCSEV	IP.JCSEV.V	IP.JCSEV.Q	IP.JCSEV.X	IP.JCSEV.G
CR	37.55%	**43.19%**	19.80%	32.71%	37.55%
AAR	11.13%	11.61%	2.05%	**11.63%**	11.13%
TR	0.82	**0.97**	0.49	0.79	0.82
SR	2.58	**2.95**	1.7	2.38	2.58

Table 17: Performance comparison of JGIND Experiments for 2015 - 2018 ($\beta = 1$)

Measure	IP.JGIND	IP.JGIND.V	IP.JGIND.Q	IP.JGIND.X	IP.JGIND.G
CR	2.53%	-0.61%	1.47%	2.50%	**3.75%**
AAR	20.80%	12.84%	2.02%	**22.43%**	21.49%
TR	0.1	-0.03	0.05	**0.13**	**0.13**
SR	0.06	-0.02	0.04	0.04	**0.08**

Table 18: Performance comparison of JCSEV Experiments for 2015 - 2018 ($\beta = 1$)

Measure	IP.JCSEV	IP.JCSEV.V	IP.JCSEV.Q	IP.JCSEV.X	IP.JCSEV.G
CR	**9.49%**	7.69%	5.52%	6.30%	6.82%
AAR	6.33%	5.78%	6.70%	**6.73%**	4.94%
TR	**0.25**	0.21	0.17	0.2	0.18
SR	**0.5**	0.35	0.33	0.28	0.30

Services sector when tested on the JSE, particularly with lower β values. Table 15, 16, 17 and 18 provide a portfolio performance comparison of the base *INVEST*, the extended system and ablation experiments. We conclude that there is reasonable evidence to include systematic risk in the network. Furthermore, we conclude that the Value BN contributes to increased portfolio performance for $\beta = 0.2$ and therefore provides tentative evidence for extending the *INVEST* framework with a particular focus on the Value BN. Furthermore, we conclude that the GNN has a positive impact on system performance if the holding period is closely aligned with the horizon. This research provides a solid foundation for further investigation and extension of the *INVEST* system and other Semantic BN-based IDSSs for share evaluation.

6 LIMITATIONS AND FUTURE WORK

This research has illustrated that the *INVEST* framework is a successful IDSS for JSE share evaluation. Several observations from our results present opportunities for further investigation. The GNN could be replaced with another machine learning model to perform price prediction that aligns with the holding period of shares for short to medium-term predictions. Given the demonstrated importance of the Value BN, it could be extended with additional factors to improve performance, or weighted differently in the decision topology. Lastly, the system can be evaluated over additional holding periods and JSE sectors.

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A *INVEST* EXTENDED ONTOLOGY XML


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</Ontology>
```

B *INVEST* EXPERIMENTAL RESULTS (2015 - 2018)

Table 19: Annual returns of INVEST-recommended investment portfolio and JGIND benchmark index for General Industrials sector ($\beta = 0.2$)

Period	IP Size	IP AR	JGIND AR	Excess Return
2015 - 16	3	-19.76%	**-7.80%**	-11.96%
2016 - 17	9	**53.87%**	15.99%	37.88%
2017 - 18	1	1.92%	**13.76%**	-11.84%

Table 20: Annual returns of INVEST investment portfolio and JCSEV benchmark index for Consumer Services sector ($\beta = 0.2$)

Period	IP Size	IP AR	JCSEV AR	Excess Return
2015 - 16	2	**21.63%**	-4.15%	25.78%
2016 - 17	15	**11.76%**	-4.84%	16.60%
2017 - 18	0	0.00%	**11.48%**	-11.48%

Table 21: Annual returns of INVEST investment portfolio and JGIND benchmark index for General Industrials sector ($\beta = 0.6$)

Period	IP Size	IP AR	JGIND AR	Excess Return
2015 - 16	7	-10.06%	**-7.80%**	-2.26%
2016 - 17	4	**53.87%**	15.99%	37.88%
2017 - 18	8	**16.01%**	13.76%	2.25%

Table 22: Annual returns of INVEST investment portfolio and JCSEV benchmark index for Consumer Services sector ($\beta = 0.6$)

Period	IP Size	IP AR	JCSEV AR	Excess Return
2015 - 16	6	**-1.43%**	-4.15%	2.72%
2016 - 17	15	**11.76%**	-4.84%	16.60%
2017 - 18	7	6.24%	**11.48%**	-5.24%

Table 23: Annual returns of INVEST investment portfolio and JGIND benchmark index for General Industrials sector ($\beta \geq 1$)

Period	IP Size	IP AR	JGIND AR	Excess Return
2015 - 16	9	-7.48%	**-7.80%**	0.32%
2016 - 17	4	**53.87%**	15.99%	37.88%
2017 - 18	8	**16.01%**	13.76%	2.25%

Table 24: Annual returns of INVEST investment portfolio and JCSEV benchmark index for Consumer Services sector ($\beta \geq 1$)

Period	IP Size	IP AR	JCSEV AR	Excess Return
2015 - 16	10	-8.20%	**-4.15%**	-4.05%
2016 - 17	15	**11.76%**	-4.84%	16.60%
2017 - 18	13	**15.43%**	11.48%	3.95%

Table 25: Performance comparison of INVEST investment portfolio on noisy data ($\beta = 0.2$)

Measure	IP.JGIND	IP.JGIND.N	IP.JCSEV	IP.JCSEV.N
CR	13.33%	**36.91%**	37.55%	**38.75%**
AAR	12.01%	**13.54%**	11.13%	**11.48%**
TR	0.37	**1.06**	0.82	**0.98**
SR	0.25	**0.61**	**2.58**	1.34

Table 26: Annual returns of Value Evaluation network investment portfolio and INVEST investment portfolio for General Industrials sector ($\beta = 0.2$)

Period	IP Size	JGIND.V	IP.JGIND	Excess Return
2015 - 16	3	-27.20%	**-19.76%**	-7.44%
2016 - 17	9	40.67%	**53.87%**	-13.20%
2017 - 18	1	1.92%	1.92%	0%

Table 27: Annual returns of Value Evaluation network investment portfolio and INVEST investment portfolio for Consumer Services sector ($\beta = 0.2$)

Period	IP Size	JCSEV.V	IP.JGIND	Excess Return
2015 - 16	2	21.60%	**21.63%**	-0.03%
2016 - 17	17	**13.90%**	11.76%	2.14%
2017 - 18	0	0%	0	0%

Table 28: Annual returns of Value Evaluation network investment portfolio and INVEST investment portfolio for General Industrials sector ($\beta = 1$)

Period	IP Size	JGIND.X	IP.JGIND	Excess Return
2015 - 16	15	-17.68%	**-7.48%**	-10.20%
2016 - 17	9	40.67%	**53.87%**	-13.20%
2017 - 18	10	15.53%	**16.01%**	-0.48%

Table 29: Annual returns of Value Evaluation network investment portfolio and INVEST investment portfolio for Consumer Services sector ($\beta = 1$)

Period	IP Size	JCSEV.X	IP.JCSEV	Excess Return
2015 - 16	12	-11.28%	**-8.20%**	-3.08%
2016 - 17	17	**13.90%**	11.76%	2.14%
2017 - 18	13	15.43%	15.43%	0%

Table 30: Annual returns of Quality Evaluation network investment portfolio and INVEST investment portfolio for General Industrials sector ($\beta = 0.2$)

Period	IP Size	JGIND.Q	IP.JGIND	Excess Return
2015 - 16	2	-19.76%	-19.76%	-0%
2016 - 17	12	-7.59%	**53.87**	-61.46%
2017 - 18	1	1.92%	1.92	0%

Table 31: Annual returns of Quality Evaluation network investment portfolio and INVEST investment portfolio for Consumer Servies sector ($\beta = 0.2$)

Period	IP Size	JCSEV.Q	IP.JGIND	Excess Return
2015 - 16	3	-2.86%	**21.63%**	-24.49%
2016 - 17	17	**12.01%**	11.76%	0.25%
2017 - 18	1	-0.30%	0%	-0.30%

Table 32: Annual returns of Quality Evaluation network investment portfolio and INVEST investment portfolio for General Industrials sector ($\beta = 1$)

Period	IP Size	JGIND.X	IP.JGIND	Excess Return
2015 - 16	12	-12.82%	**-7.48%**	-5.34%
2016 - 17	12	-7.59%	**53.87%**	-61.46%
2017 - 18	13	**26.47%**	16.01%	10.46%

Table 33: Annual returns of Quality Evaluation network investment portfolio and INVEST investment portfolio for Consumer Services sector ($\beta = 1$)

Period	IP Size	JCSEV.X	IP.JCSEV	Excess Return
2015 - 16	17	**-6.04%**	-8.20%	2.16%
2016 - 17	17	**12.01%**	11.76%	0.25%
2017 - 18	17	14.12%	**15.43%**	-1.31%

Table 34: Annual returns of INVEST + Systematic Risk investment portfolio and INVEST investment portfolio for General Industrials sector ($\beta = 0.2$)

Period	IP Size	JGIND.X	IP.JGIND	Excess Return
2015 - 16	1	**76.65%**	-19.76%	96.41%
2016 - 17	2	**68.20%**	53.87%	14.33%
2017 - 18	1	1.92%	1.92	0%

Table 35: Annual returns of INVEST + Systematic Risk investment portfolio and INVEST investment portfolio for Consumer Services sector ($\beta = 0.2$)

Period	IP Size	JCSEV.X	IP.JCSEV AR	Excess Return
2015 - 16	1	18.95%	**21.63**%	-2.68%
2016 - 17	8	**15.93%**	11.76%	4.17%
2017 - 18	0	0.00%	0%	0%

Table 36: Annual returns of INVEST + Systematic Risk and INVEST investment portfolio for General Industrials sector ($\beta = 1$)

Period	IP Size	JGIND.X	IP.JGIND	Excess Return
2015 - 16	5	**-4.33%**	-7.48%	3.05%
2016 - 17	2	**68.2**%	53.87%	14.33%
2017 - 18	4	3.52%	**16.01%**	-12.49%

Table 37: Annual returns of INVEST + Systematic Risk and INVEST investment portfolio for Consumer Services sector ($\beta = 1$)

Period	IP Size	JCSEV.X	IP.JCSEV	Excess Return
2015 - 16	8	-10.84%	**-8.20%**	-2.64%
2016 - 17	8	**15.93%**	11.76%	4.17%
2017 - 18	8	15.11%	**15.43%**	-0.32%

Table 38: Annual returns of INVEST and INVEST + GNN investment portfolio over 1 year for General Industrials sector ($\beta = 0.2$)

Period	IP Size	JGIND.G	IP.JGIND	Excess Return
2015 - 16	2	-19.76%	-19.76%	0%
2016 - 17	4	53.87%	53.87%	0%
2017 - 18	1	1.92%	1.92	0%

Table 39: Annual returns of INVEST and INVEST + GNN investment portfolio over 1 year for Consumer Services sector ($\beta = 0.2$)

Period	IP Size	JCSEV.G	IP.JCSEV AR	Excess Return
2015 - 16	2	21.63%	21.63%	0%
2016 - 17	15	11.76%	11.76%	0%
2017 - 18	0	0.00%	0%	0%

Table 40: Annual returns of INVEST and INVEST + GNN investment portfolio over 1 year for General Industrials sector ($\beta = 1$)

Period	IP Size	JGIND.G	IP.JGIND	Excess Return
2015 - 16	9	-7.48%	-7.48%	0%
2016 - 17	4	53.87%	53.87%	0%
2017 - 18	10	**18.08%**	16.01%	2.07%

Table 41: Annual returns of INVEST and INVEST + GNN investment portfolio over 1 year for Consumer Services sector ($\beta = 1$)

Period	IP Size	JCSEV.G	IP.JCSEV	Excess Return
2015 - 16	11	-12.38%	**-8.20%**	-4.18%
2016 - 17	15	11.76%	11.76%	0%
2017 - 18	13	15.43%	15.43%	0%

Table 42: Annual returns of INVEST and INVEST + GNN investment portfolio over 1-month for General Industrials sector($\beta = 0.2$)

Period	IP Size	JGIND.G	IP.JGIND	Excess Return
2015 - 16	2	-0.31%	-0.31%	0%
2016 - 17	4	-3.91%	-3.91%	0%
2017 - 18	1	20.13%	20.13%	0%

Table 43: Annual returns of INVEST and INVEST + GNN investment portfolio over 1-month for Consumer Services sector ($\beta = 0.2$)

Period	IP Size	JCSEV.G	IP.JCSEV AR	Excess Return
2015 - 16	2	8.47%	8.47%	0%
2016 - 17	15	-0.64%	-0.64%	0%
2017 - 18	0	0%	0%	0%

Table 44: Annual returns of INVEST and INVEST + GNN investment portfolio over 1-month for General Industrials sector ($\beta = 1$)

Period	IP Size	JGIND.G	IP.JGIND	Excess Return
2015 - 16	9	-0.98%	-0.98%	0%
2016 - 17	4	-3.91%	-3.91%	0%
2017 - 18	6	**6.22%**	0.21%	6.01%

Table 45: Annual returns of INVEST and INVEST + GNN investment portfolio over 1-month for Consumer Services sector ($\beta = 1$)

Period	IP Size	JCSEV.G	IP.JCSEV	Excess Return
2015 - 16	11	0.43%	**0.48**	-0.05%
2016 - 17	15	-0.64%	-0.64%	0%
2017 - 18	13	3.40%	3.40%	0%