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INVESTMENT IMPLICATIONS OF INDUSTRY 4.0: EVIDENCE FROM SMART MANUFACTURING ETFS

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Abstract. The rise of smart manufacturing, driven by digital transformation and Industry 4.0, has introduced new opportunities for investors seeking to diversify their portfolios. Smart manufacturing ETFs offer a unique risk-return profile tailored to the evolving landscape of industrial automation and data-driven processes. This paper explores the comparative risk-adjusted performance of a smart manufacturing ETF, a conventional industrial portfolio, and a broad-market SP500 tracking portfolio, utilizing daily data from October 2019 to October 2022. By deconstructing the excess returns of these portfolios through one-factor, three-factor, and five-factor asset pricing models, we provide insights into the risk exposure and performance drivers of smart manufacturing investments. Results indicate that investing in smart manufacturing, while less performant relative to the other investments, carries less exposure to market risk and can provide important diversification benefits to equity portfolios. Moreover, there is a positive loading for the size factor and a negative loading for the value and profitability factors for the smart manufacturing portfolio during a period of positive premium for all factors except for size. This implies that the consequent payoff in terms of profitability will eventually turn the loading of the profitability factor into positive territory, increasing returns on smart manufacturing investing.

Keywords: smart manufacturing, pricing factors, factor models, portfolio investment, market risk, diversification.

JEL Classification: G11, G12, O33.

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1. Introduction and research background

Data driven processes have become the linchpin of advanced goods production flows, disrupting the predominant industrial paradigm. The manufacturing sector has recognized the benefits of digitalization and technological transformation of production processes and supply chains, part of what is known as Industry 4.0 and smart manufacturing (Ghobakhloo, 2020). Smart manufacturing represents a paradigm shift in industrial production that relies on the use of advanced digital technologies to create adaptive, intelligent and highly integrated manufacturing systems. At its core, smart manufacturing refers to various systems such as cyber-physical platforms, Internet of Things (IoT) devices, artificial intelligence, and big data analytics that support real-time monitoring, predictive maintenance, and autonomous decision-making in the production process (Kang et al., 2016; Zhong et al., 2017). These systems enable horizontal and vertical integration of production processes (Lu, 2017) and incorporate human-machine collaboration interfaces and cloud-based data storage to achieve higher efficiency and quality of industrial production (Mahmoodi et al., 2024). Smart factories can further optimize production efficiency and minimize errors by integrating informational technology (Namjoshi & Rawat, 2022) and create a network of highly connected data-driven factories where information between plants and machines is bridged and dynamic optimization process optimization is achieved (Papazoglou & Andreou, 2019). The adoption of computerized systems and processing units to replace human labor, a radical departure from traditional industrial processes, is likely the driving force behind the transition to a more profitable smart manufacturing model (Madykh & Okhten, 2018).

The concept of Industry 4.0 encompasses various informational technologies, specifically the Internet of Things and services that can help increase the productivity of industrial activities. The most referred technologies that are recognized as drivers of the fourth Industrial Revolution are the Internet of Things (IoT), Big Data Analytics (BD), The Cloud (Cloud Computing), Additive Manufacturing (3D Printing), Augmented Reality, Simulation, Autonomous robots and System Integration (Rüßmann et al., 2015). The purpose of Industry 4.0 is to enhance manufacturing processes and establish production chains using Cyber-Physical Systems (Kagermann et al., 2013), while improving the quality of end-products, performance and efficiency, and optimizing production cost (Kamble et al., 2018). Moreover, it can improve work-life balance and employee satisfaction (Kagermann et al., 2013). Operational efficiency can see improvements in low-tech enterprises due to a greater scope of automation (Jang et al., 2022), creating an appeal for investments in previously neglected activities. Existing literature outlines the benefits of these strategies to transform traditional manufacturing processes – see, for example, Ingaldi and Ulewicz (2020), Ren et al. (2019), Kusiak (2019).

Among the few scholarly endeavors that linked smart manufacturing to enhanced business performance, Somohano-Rodríguez and Madrid-Guijarro (2022) evaluated the influence of investing in five components of smart manufacturing on enterprises' profitability, revenues, and labor performance on a sample of 275 SMEs between 2005 and 2018 but achieved mixed or inconclusive results. Arcidiacono and Schupp (2024) argued that rather than translating into increased financial performance, the adoption of smart manufacturing technologies leads to improvements in operational performance dimensions such as cost reduction, quality, flexibility, that help firms maintain their competitive. In contrast, Kim et al. (2023) showed that beside the managerial and operational improvements, the financial dimensional registers the greatest improvement from smart manufacturing adoption. Furthermore, Yuan et al. (2022) investigated the effect of Supply Chain Innovation (SCI) announcements linked with Industry 4.0 and Industry 5.0 and discovered that they increase shareholder value, although it seems the manufacturing sector is less attractive than the services sector for investors, due to a possible lacking comprehension of its benefits (Gutkevych, 2019).

In this setting, it is critical to have a complete and accurate understanding of how smart manufacturing or Industry 4.0 strategies influence the performance of corporate adopters. The interest in studying the performance of Industry 4.0 stocks stems from the need to understand how smart adaptations and innovations generate a positive output in the business cycle and present investors with the prospect of earning a return from non-conventional industry investments. Although it is difficult to assess the future payoffs of investing in emerging technologies due to uncertainty in the implementation cost and means of adopting and further diffusing them (Benaroch & Kauffman, 1999), this is a significant incentive for the study.

Jang et al. (2022) show that superior financial results are linked to increases in the maturity of smart manufacturing projects, regardless of the technologization level of the enterprise, and a successful large-scale adoption of the Industry 4.0 paradigm strongly depends on outside social influences and the development of smart manufacturing adopters throughout the value chain (Kim et al., 2023). The results may be of significant interest to investors that explore moving away from conventional manufacturing and towards emerging technology focused industry sectors. Furthermore, understanding the underlying stock price mechanism of smart manufacturing can help businesses strategically plan their life cycle and offer an eagle eye over how Industry 4.0 would react to the market. Equally important, recognizing the forces that drive the performance of enterprises immersed in Industry 4.0 may help policymakers build appropriate and tailored stimuli to encourage their development.

While there is no outstanding financial market definition for labeling smart manufacturing investments, the Exchange Traded Fund (ETF) we used as proxy and the index it tracks offer an investment opportunity into a portfolio of companies characterized by the transformation of the manufacturing and industrial processes through disruptive technologies, one of which must be Advanced Robotics, Cloud & Big Data, Cyber Security, Augmented Reality and 3D Printing, and IoT (Amundi Asset Management, 2023; Solactive, 2025), suitable for what is commonly recognized as a thematic ETF. Thematic ETFs and sector-focused ETFs are distinct categories of investment instruments characterized by cost-efficiency and accessibility towards retail investors (Goel et al., 2024) that target specific economic areas or business features (Joshi & Dash, 2024; Luft & Plamondon, 2017; Methling & Von Nitzsch, 2018). According to Methling and Von Nitzsch (2018), thematic ETFs are appropriate means for tracking economic developments tied to megatrend that such as disruptive technology, demographic or demand shifts, while sector ETF are preferred by investors who seek to increase exposure in one economic segment (Luft & Plamondon, 2017). Technology and Smart Manufacturing can be closely matched as themes based on their shared focus on stocks influenced by innovation and technological transformation. Thematic elements help diversify an investor's portfolio by creating a satellite – core relationship between the thematic and conventional ETFs (Methling & Von Nitzsch, 2018). The recent leading performance of Sustainable and Green ETFs made them stand out as an example of successful thematic assets (Joshi & Dash, 2024). ETFs labelled as such aim to curate investments in stocks with positive environmental, social, and governance (ESG) attributes that align the United Nations Sustainable Development Goals (Marín-Rodríguez et al., 2025). Analyzing volatility, liquidity, risk-return trade-offs, tracking errors (Joshi & Dash, 2024) and conducting factor-based analysis of ETFs through models like CAPM and Fama-French (Pavlović et al., 2025) have proved useful in understanding the drivers of performance for these specific investment areas. Methling and Von Nitzsch (2018) believes that yield enhancements of thematic ETFs is linked to their individuality and are weakened by their correlation to the broader market, an assumption which is reinforced by the potential of outperforming the market by adopting sector momentum strategies that rely on sector ETFs in terms of absolute return (Joshi & Dash, 2024).

Investors recognize that cyclical economic downturns are a significant concern for stock trading, and for industry stocks the heterogeneous price fluctuations they exhibit during such periods complicate their integration in risk-adjusted portfolios (Baele & Londono, 2013). However, under the right circumstances, industry stocks can provide a hedging opportunity from market-wide drops (Liu et al., 2018). Research shows that industrial stocks' price behavior differs from other sectorial assets due to their sensitivity to macroeconomic factors (Bianchi et al., 2017) and perceived global market integration and responsiveness to global factor variation (Szczygielski et al., 2020). Manufacturing and industry stock returns have combined liquidity and industrial real output growth integrators and tracked the market (Bianchi et al., 2017). Stock prices in the same industry tend to move together and differently from other industries (Contreras et al., 2017) and depend on the country's market structure (Dutt & Mihov, 2008).

After Sharpe (1964) and Lintner (1965) developed the Capital Asset Pricing Model (CAPM) to explain that higher returns are driven by higher risk exposure to overall market risks, theoretical and empirical literature on asset pricing models has grown significantly. The model was extensively empirically examined Fama and French (2004), and its mixed reliability evidence stimulated scholars' interest for multifactor asset pricing models. Thus, the Fama-French Three-Factor model (FF3) improved the Sharpe one-factor model by accounting for average market return, size, and book-to-market value risk factors – the market factor is similar to the CAPM depiction, the size factor is the difference in mean returns between small- and large-capitalization stocks, and the book-to-market value factor is the difference between high- and low-book-to-value stocks (Fama & French, 1993). Fama and French (1995) suggested that size factors enhance small stock return variability and that smaller enterprises are less profitable. They also found that overvalued capital market stocks have higher volatility but also higher average returns, that book-to-market ratio changes can be explained by long-term profitability variations, and that underpriced stocks indicate cash flow downturns. FF3 established itself as an alternative in the field of multifactor asset pricing models and led to several offshoots such as the Carhart (1997) four-factor model – which accounts for the momentum effect in stocks' returns – and the Fama-French five-factor model (FF5) – see Fama and French (2015). The newly included factors are operational "profitability" and "investment", represented by the difference in returns of stocks with robust and weak profitability (RMW), and conservative and aggressive investment (CMA), respectively. Empirical testing of the model showed that it performs well in both developed and emerging markets, explaining between 71% and 94% of the cross-section variance of expected returns (Fama & French, 2015; Foye, 2018; Huang, 2019), which makes it a solid tool to assess stock performance.

When applied to stocks from the manufacturing or technology sectors, Sarwar et al. (2018) found that FF5 yields better results for US portfolios than FF3, particularly for the high-tech ETFs. Assets linked to good health, well-being, infrastructure, industry and innovation tend to perform better than assets relating to other global goals, a signal that sectors such as healthcare, biotechnology (Miralles-Quirós et al., 2020) and smart manufacturing are promising investment destinations that preserve the environment. This is further supported by Faff (2004), who found that smaller businesses benefited from operations in the engineering, healthcare, and biological fields.

This study examines the risk-adjusted returns of three investment portfolios: a smart manufacturing ETF, a traditional industrial sector portfolio, and a broad-market S&P 500 index fund, using daily performance data spanning from October 2019 through October 2022. Through the application of one-factor, three-factor, and five-factor asset pricing frameworks to analyse excess returns, this research reveals the underlying risk characteristics and performance determinants that drive smart manufacturing investment outcomes. This work makes an original contribution to the literature by investigating the risk-return profile of smart manufacturing investments through the lens of asset pricing models, specifically FF5. While prior studies have investigated the relevance of Industry 4.0 for business operations efficiency, only a few have tackled its financial markets implications. Considering this significant research gap, the study is the first comprehensive asset pricing analysis of smart manufacturing ETFs that applies multi-factor asset pricing models specifically to smart manufacturing investment vehicles. This approach departs from previous studies that have mainly focused on operational efficiency benefits associated with the adoption of Industry 4.0. To our knowledge, no prior study has explored the risk-return profile of diversified smart manufacturing portfolios using well-grounded financial theory frameworks. In this framework, a major contribution is the detection of distinct risk factor exposures for smart manufacturing portfolios, particularly their positive loading on the size factor and negative loadings on value and profitability factors. Our findings thus reveal that smart manufacturing companies tend to be smaller in size and growth-oriented, characterised by lower profitability, which diverges from traditional industrial sector investment features. Moreover, the study empirically demonstrates and quantifies the diversification potential of smart manufacturing investments, showing their lower exposure to market risk and increased resilience during economic downturns. The lower coefficient of systematic risk (beta) for smart manufacturing portfolio compared to traditional industrial investments offers concrete proof of the reduced exposure to systematic risks of the former. Additionally, this research introduces a forward-looking analytical framework that supports a reversal of the current negative profitability loadings as Industry 4.0 investments mature. Thus, it creates a temporal dimension that is absent from the previous analysis of the performance in the manufacturing sector. Proposing an integration of Industry 4.0 research and financial market analysis, the paper draws valuable insights for strategic management, investors, portfolio managers, and policymakers that seek to understand the financial viability of smart manufacturing and further incorporate it into their decision-making process. This interdisciplinary approach strengthens the study's contribution to both industrial and technological innovation, on the one hand, and management literature, on the other hand.

Considering the research background and the identified research gap, we have formulated the following hypotheses circumscribed to the research question:

H1: Smart manufacturing portfolios exhibit significantly different risk factor exposures compared to conventional industrial portfolios.

H2: Smart manufacturing portfolios provide superior diversification benefits compared to conventional industrial portfolios.

H3: The Fama-French five-factor model explains well return variation for smart manufacturing portfolios as well as for conventional industrial and broad market portfolios.

The following structure is proposed throughout the remainder of the text. Section 2 discusses the data used and the research methodology. Section 3 summarizes the main findings and Section 4 evaluates their significance, contrasts them with existing research, and contextualizes them. The final section of the report debriefs the main findings, outlines research contributions and suggests valuable future research directions.

2. Materials and methods

2.1. Data

The daily prices for three relevant ETFs are sourced from Yahoo Finance. We sourced daily prices for Amundi Smart Factory ETF (ticker "SFTRY.PA"), a smart manufacturing ETF that tracks the performance of the Solactive Smart Factory Index and stands for the Smart Manufacturing portfolio (hereafter SM) analyzed in the study. The major selection criterion for the smart manufacturing ETF is data availability, i.e., a sufficient trading history that allows for robust estimations. The SM portfolio is strongly diversified, including 272 smart factories in 30 countries engaged in either Advanced Robotics, Cloud & Big Data, Cyber Security, Augmented Reality & 3D Printing, or the Internet of Things (IoT). At the end of 2022, the fund had holdings of 38.91% in technology and industrial companies, with a global exposure – 55.04% of the funds were invested in US companies and the remaining (44.96%) in European companies. For comparative purposes, prices for a conventional or "normal" industrial portfolio are also sourced; to this end, we employ the Industrial Select Sector SPDR Fund (ticker "XLI") that offers an effective representation of the industrial sector of the S&P 500 Index as our conventional (i.e., as opposed to "smart") industrial portfolio. The conventional portfolio includes a total of 70 companies engaged in the following industries: aerospace and defense; industrial conglomerates; marine; transportation infrastructure; machinery; road and rail; air freight and logistics; commercial services and supplies; professional services; electrical equipment; construction and engineering; trading companies and distributors; airlines; and building products. Moreover, we collect daily prices for the SPDR S&P 500 ETF (ticker "SPY"), which tracks the performance of the S&P 500 Index and will serve to inform the risk-return profile of competitive portfolios. Additionally, the prices for the Amundi Smart Factory ETF are converted to USD to match the currency of the XLI and SPY. Finally, all daily ETF price series are transformed into daily logarithmic return series.

Figure 1 provides a graphical depiction of the evolution of the smart manufacturing portfolio from inception until the end of October 2022, along with relevant competitor portfolios, including "normal" industrial investments and the S&P500 portfolio that proxies the evolution of the US equity market.

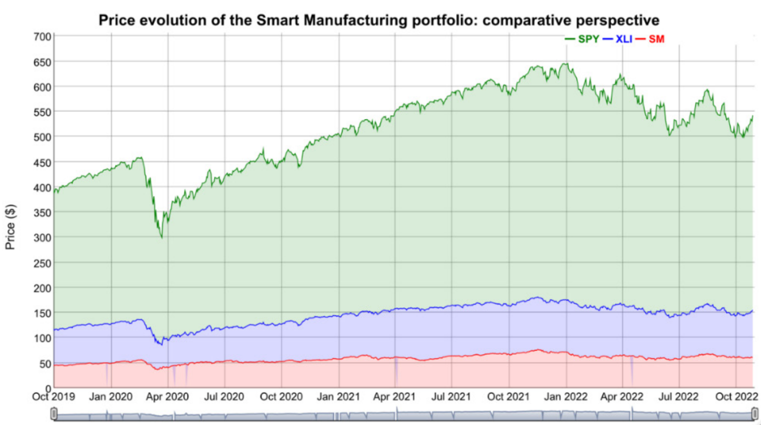

Figure 1. Price evolution of the three investment funds (1.10.2019 – 31.10.2022)

The three portfolios show similar trends. After its launch, the SM portfolio's price rose steadily until February 2020, when the COVID-19 pandemic hit and it fell to its lowest point by mid-March 2020. After that, it performed well until 2021, earning negative returns due to the Russian-Ukrainian conflict that has harmed global equities markets. The XLI and SPY portfolios show similar patterns, but more pronounced trends. Figure 2 shows the daily return series for the three portfolios over the same period. The smart manufacturing portfolio has lower volatility.

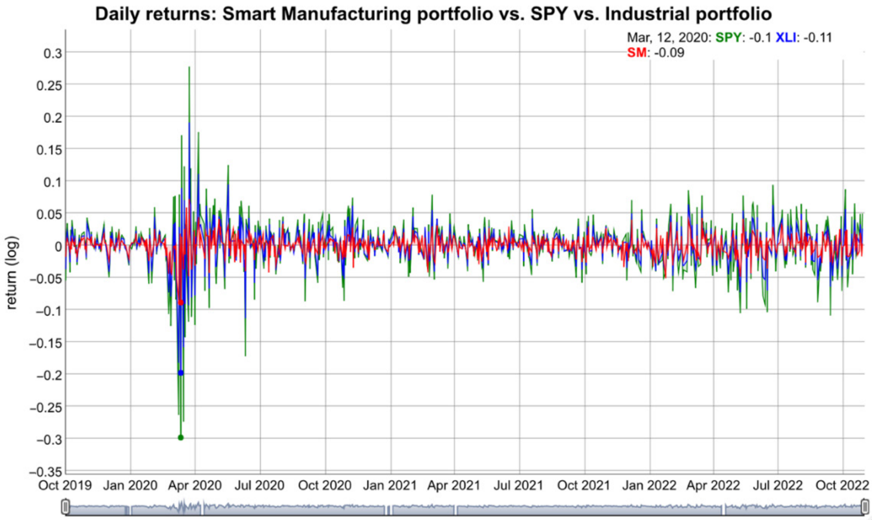

Figure 2. Price returns of the three investment funds (1.10.2019 – 31.10.2022)

Subsequently, the daily Global Fama-French five factors are obtained from Kenneth French's Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5developed.html). All factor returns are given in USD and are adjusted for dividends.

The market risk premium (MKT) is estimated by deducting the U.S. one-month T-bill rate from the value-weighted market portfolio of the "global" market, which includes 23 countries (i.e., Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Hong Kong, Ireland, Italy, Japan, the Netherlands, Norway, New Zealand, Portugal, Sweden, Singapore, and the United States).

MKT for July of year t to June of t+1 includes all stocks for which market equity data for June of t. is available. Similarly, the other four factors, respectively SMB (Small minus Big), HML (High minus Low), RMW (Robust minus Weak), and CMA (Conservative minus Aggressive) for July of year t to June of t+1 include all stocks for which the following data is available: market equity data for December of t-1 and June of t, (positive) book equity data for t-1 (for SMB, HML, and RMW), non-missing revenues and at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense for year t-1 (for SMB and RMW), and total assets (TA) for years t-2 and t-1 (for SMB and CMA). Further, as French explains, the factors (2 x 3) are produced by sorting all available stocks into two sizes (i.e., market capitalization) and three book-to-market equity (B/M), three operating profitability (OP), and three investment (INV) groups at the end of each June. The big-size portfolio comprises the top 90% of market capitalization in the 23 countries, whereas the small-size portfolio is comprised of the bottom 10%. Furthermore, the B/M, OP, and INV breakpoints are the 30th and 70th percentiles of respective ratios for the big stocks in the included countries. Further relevant details for the factor construction can be retrieved from the Data Library website.

The data sample starts on 1st October 2019, as this is the inception date for the Smart Manufacturing ETF. The end date of the sample is 31 October 2022, translating into a minimum of 743 daily observations for each series.

2.2. Method

The main purpose of this study is to uncover pricing factors for smart manufacturing investments. To this end, we evaluate the performance of alternative models commonly employed in asset pricing research using a relevant smart manufacturing portfolio. We also perform the same analysis for a "normal" industrial portfolio, thus offering relevant new evidence for market professionals regarding potential distinct risk factors for smart manufacturing investments and "normal" (i.e., "non-smart") investments in the industrial sector.

Fama and French (2015) developed a 5-factor model (FF5) to account for the market, size, value, profitability, and investment patterns in predicted stock returns. They demonstrate that this model, including two new factors standing for profitability and investment as in Eq. (3), improves on the empirical performance of their traditional 3-factor model (FF3) (Fama & French, 1993). In turn, FF3, given in Eq. (2), augments the Capital Asset Pricing Model (CAPM) specified in Eq. (1) with two new factors proxying for size and value.

Consequently, Fama and French propose the improvement of the traditional market model through two successive steps, going from Eq. (1) to Eq. (3) via Eq. (2).

$$R_{it} - R_{ft} = \beta_{0i} + \beta_{1i}\left(R_{mt} - R_{ft}\right) + u_{it}; \quad (1)$$

$$R_{it} - R_{ft} = \beta_{0i} + \beta_{1i}\left(R_{mt} - R_{ft}\right) + \beta_{2i}\left(SMB_t\right) + \beta_{3i}\left(HML_t\right) + u_{it}; \quad (2)$$

$$R_{it} - R_{ft} = \beta_{0i} + \beta_{1i}\left(R_{mt} - R_{ft}\right) + \beta_{2i}\left(SMB_t\right) + \beta_{3i}\left(HML_t\right) + \beta_{4i}\left(RMW_t\right) + \beta_{5i}\left(CMA_t\right) + u_{it}; \quad (3)$$

$$R_{it} - R_{ft} = \beta_{0i} + \beta_{1i}\left(R_{mt} - R_{ft}\right) + \beta_{2i}\left(SMB_t\right) + \beta_{3i}\left(HML_t\right) + \beta_{4i}\left(RMW_t\right) + \beta_{5i}\left(CMA_t\right) + u_{it}, \quad (4)$$

where R_{it} denotes the portfolio i return and R_{ft} is the rate of return for the risk-free asset, so the left-hand side of each equation represents the excess return of portfolio i, with i alternatively standing for the smart manufacturing portfolio (SFTRY.PA) and the "normal" industrial portfolio (XLI). The right-hand side of the CAPM in Eq. (1) includes the market excess return (MKT) (i.e., R_{mt} is the market rate of return), while β_{1i} reflects the systematic risk characterizing the portfolio. In the FF3 model depicted in Eq. (2), the right-hand side proposes three explanatory factors, respectively the market excess return, the size factor SMB_t (i.e., small capitalization minus big capitalization portfolios), and the value factor HML_t (i.e., high book-to-market ratio minus low book-to-market ratio). Finally, FF5 (Eq. (3)) augments FF3 with two additional factors reflecting profitability (RMW_t extracts weak operating profitability portfolios from robust operating profitability portfolios) and investment (i.e., CMA_t calculated as conservative investment portfolios minus aggressive investment portfolios). In all equations, u_t is the normally distributed error term, and t = 1, 2, ..., T. For model comparison purposes, we rely on the adjusted R-squared as well as on the AIC and BIC criteria.

3. Results

Table 1 reports the main descriptive statistics for the three portfolios included in the empirical investigations. Smart manufacturing investments have reduced mean values, volatility, and returns that are closer to a normal distribution over the period under review. The smart manufacturing portfolio has average daily returns of 0.03% with a median of 0.13%, at a total risk (standard deviation) of 1.56%, while the SP500 tracking portfolio has average excess returns of 0.04% with a median of 0.13%. In contrast, the "normal" industrial portfolio has the most volatility (standard deviation of 1.7%), the highest average return than the SPY, and the lowest median value of 0.11%. All portfolios had a median return greater than the mean, indicating a "skewed to the left" long tail of low values.

Table 1. Descriptive statistics for the smart manufacturing, "Normal" industrial, and SP500 portfolios

	Smart manufacturing portfolio (SFTRY.PA)	"Normal" industrial portfolio (XLI)	SP500 portfolio (SPY)
Minimum	–0.0884	–0.1204	–0.1159
Quartile 1	–0.0076	–0.0068	–0.0057
Median	0.0013	0.0011	0.0013
Mean	0.0003	0.0005	0.0004
Quartile 3	0.0092	0.0082	0.0079
Maximum	0.0720	0.1191	0.0867
Standard deviation	0.0156	0.0170	0.0154
Skewness	–0.5435	–0.6327	–0.8841
Kurtosis	3.4629	11.2279	10.7636

Table 2 shows the three portfolios' risk-adjusted performance. Risk (proxied by standard deviation, VaR, and expected shortfall (ES)) and total return are traded off in different Sharpe ratios, with larger ratios implying better return performance for the same risk. Also, the SM portfolio has lower VaR and standard deviation Sharpe ratios than the SP500 tracker SPY and the industrial portfolio XLI. When returns are adjusted for projected shortfall as a risk proxy, the SM portfolio outperforms the other two. Based on downside semi-variance, the Sortino ratio (Sortino & Price, 1994) is a better risk-adjusted performance statistic in the "loss aversion" framework than in the "risk aversion" concept. Yu et al. (2006) suggest that investors are more concerned with loss than gain in this setting. According to estimates, the SM portfolio has a lower Sortino ratio (0.0352) than the SPY and XLI portfolios (0.0397 and 0.0368, respectively).

Table 2. Risk-adjusted performance of the three investment funds

	Smart manufacturing portfolio (SFTRY.PA)	"Normal" industrial portfolio (XLI)	SP500 portfolio (SPY)
StdDev Sharpe (Rf = 0%, p = 95%, Annualized)	0.2986	0.3000	0.3589
VaR Sharpe (Rf = 0%, p = 95%, Annualized)	2.7924	3.0448	3.4866
ES Sharpe (Rf = 0%, p = 95%, Annualized)	1.6040	1.4240	1.4641
Sortino (MAR = 0%)	0.0352	0.0368	0.0397

Table 3 sheds further light on the downside risk of the three portfolios by estimating several metrics that are acknowledged as more useful risk analysis tools for non-normally distributed assets. Semi-deviation and downside deviation reduce positive returns from risk calculations. Both metrics measure underperformance below a baseline rate and show that the smart manufacturing portfolio is safer than the industrial portfolio. The former utilizes the mean return, or zero, whereas the later employs Sharpe's Minimum Acceptable Return. Alternative investment downside risk can also be assessed by analysing drawdowns, which show the loss from peak value. The maximum drawdown statistic estimates an asset's worst cumulative loss across the analysis period (Peterson et al., 2024). The SM portfolio had a 35.78% maximum drawdown, close to the SP500 portfolio's 35.75%, but substantially lower than the conventional industrial portfolio's 44.11% cumulative loss. The modified Cornish-Fisher Value at Risk measure (Modified VaR) incorporates skewness and kurtosis via analytical estimation using a Cornish-Fisher expansion (Favre & Galeano, 2002; Huisman et al., 1998) and is estimated, along with the modified expected shortfall (Modified ES) – see Uryasev (2000) and Scherer and Martin (2005). ES assesses the average loss beyond mean-VaR and is a reliable risk predictor (Peterson et al., 2024). The modified VaR and modified ES measures show that the SM portfolio is consistently safer than the industrial portfolio, in line with the other risk metrics.

Table 3. Downside risk analysis for the three investment funds

	Smart manufacturing portfolio (SFTRY.PA)	"Normal" industrial portfolio (XLI)	SP500 portfolio (SPY)
Semi deviation	0.0117	0.0127	0.0116
Downside deviation (Rf = 0%, MAR = 0%)	0.0115	0.0125	0.0115
Maximum drawdown	0.3578	0.4411	0.3575
Modified VaR (95%)	–0.0256	–0.0269	–0.0252
Modified ES (95%)	–0.0455	–0.0575	–0.0602

Table 4 summarizes global FF5 factor daily premiums. Over the sample period, which matches the smart manufacturing fund's lifecycle, MKT, HML, RMW, and CMA showed positive premium. SMB is negative, indicating that small enterprises did not outperform big firms globally from October 2019 to October 2022. The market has the greatest daily premium (0.03%) of the five risk variables. Value and profitable enterprises with cautious investment plans outperform all other criteria, which have equivalent (on average) positive premiums. Note that small time series can affect the statistical reliability of estimates.

Table 4. Descriptive statistics for the five global factors

	MKT	SMB	HML	RMW	CMA
Mean	0.03	–0.01	0.01	0.01	0.01
Standard error	0.04	0.02	0.03	0.01	0.02
Median	0.07	–0.01	–0.05	0.01	–0.02
Standard deviation	1.27	0.52	0.83	0.35	0.50
Kurtosis	11.40	14.54	1.60	0.87	1.12
Skewness	–0.91	–1.42	0.21	0.08	0.14

Table 5 includes estimates for the time-series correlations between the five factors. A high correlation between HML and CMA is revealed, confirming that value companies tend to adopt conservative investment styles. In turn, HML is negatively related to the profitability factor, suggesting value firms tend to be non-profitable. Moreover, the negative correlation coefficient between the size and profitability factors indicates that over the turbulent three years analyzed, small companies have not been profitable. Furthermore, SMB is also negatively correlated with the market risk premium, indicating an underperformance of small firms during bull markets.

Table 5. Correlation matrix between the five global factors

	MKT	SMB	HML	RMW	CMA
MKT	1				
SMB	–0.40	1			
HML	–0.06	0.23	1		
RMW	–0.12	–0.32	–0.25	1	
CMA	–0.28	0.16	0.83	0.03	1

We use the Fama-French five-factor model to evaluate documented risk factors' impact on smart manufacturing fund performance (Eq. (3)). For comparison, the "normal" industrial portfolio and SP500 tracking portfolio are also examined. We also estimate the Sharpe (1964) and Lintner (1965) capital asset pricing model and the Fama and French (1993) three-factor model for the same investments to test model explanatory power in increasingly multifactor contexts. The portfolio return premium is the dependent variable in all estimations of the explanatory factors' excess return on the three ETFs.

Estimation results for the one-factor, three-factor, and five-factor models depicted in Eqs. (1)–(3) for the three alternative portfolios, including the Smart Manufacturing fund, are presented in Tables 6–8. According to Ross (1976) arbitrage pricing theory, regression loadings on the components should absorb the uncertainty and fully explain excess returns if the appropriate risk factors are included, consequently lowering the intercepts to zero. Of note, the intercepts in all estimated equations are undistinguishable from zero for all portfolios.

Table 6. Parameter estimates of the one-factor model

One-factor model		
Parameter	MKT	β_0
Smart manufacturing portfolio (SFTRY.PA)		
Coefficients	0.74	0.0060
Std. errors (p-value)	0.0307 (0.00)	0.0393 (0.8)
"Normal" industrial portfolio (XLI)		
Coefficients	1.19	–0.0001
Std. errors (p-value)	0.0214 (0.00)	0.0278 (0.9)
SP500 portfolio (SPY)		
Coefficients	1.14	0.0049
Std. errors (p-value)	0.0117 (0.00)	0.0152 (0.7)

The MKT factor is significant at 1% for all model settings and portfolios, indicating that market returns affect all portfolio returns. In the SP500 and XLI models, the market factor coefficient is supra-unitary, indicating greater volatility than the global market portfolio, but in the smart manufacturing portfolio, it is sub-unitary, ranging from 0.74 in the one-factor model to 0.87 in the FF3 model.

Table 7. Parameter estimates of the FF3 model

Parameter	MKT	SMB	HML	β_0
Smart manufacturing portfolio (SFTRY.PA)				
Coefficients	0.8488	0.7693	–0.4425	0.0185
Std. errors (p-value)	0.0298 (0.00)	0.0865 (0.00)	0.0436 (0.00)	0.0350 (0.6)
"Normal" industrial portfolio (XLI)				
Coefficients	1.1436	–0.4091	0.5887	–0.0114
Std. errors (p-value)	0.0180 (0.00)	0.0458 (0.00)	0.0264 (0.00)	0.0215 (0.6)
SP500 portfolio (SPY)				
Coefficients	1.0338	–0.6631	0.0187	–0.0001
Std. errors (p-value)	0.0083(0.00)	0.0212(0.00)	0.0122(0.13)	0.0099 (0.9)

The results provide evidence of positive loading of the size factor for the SM portfolio, and evidence of negative loadings of the size factor for the industrial and SP500 portfolios. Consequently, the SM ETF carries an exposure tilt towards small-cap stocks, performing better when small-size portfolios outperform large-size portfolios.

Table 8. Parameter estimates of the FF5 model

Parameter	MKT	SMB	HML	RMW	CMA	β_0
Smart manufacturing portfolio (SFTRY.PA)						
Coefficients	0.7882	0.6302	–0.3398	–0.3802	–0.2528	0.0251
Std. errors (p-value)	0.0339 (0.00)	0.0811 (0.00)	0.0912 (0.00)	0.1168 (0.00)	0.1717 (0.14)	0.0347 (0.4)
"Normal" industrial portfolio (XLI)						
Coefficients	1.1868	–0.3158	0.4991	0.2291	0.2226	–0.0176
Std. errors (p-value)	0.0204 (0.00)	0.0489 (0.00)	0.0547 (0.00)	0.0706 (0.00)	0.090 (0.01)	0.0212 (0.5)
SP500 portfolio (SPY)						
Coefficients	1.0527	–0.6340	–0.0460	0.0373	0.1342	–0.0041
Std. errors (p-value)	0.0095 (0.00)	0.0228 (0.00)	0.0255 (0.07)	0.0330 (0.25)	0.0420 (0.00)	0.0099 (0.7)

Disparities are also found in value factor influence. SM portfolio has a consistently negative premium on the value component, showing a growth style tilt, with a slope coefficient of –0.44 in FF3 and –0.34 in FF5 (significant at 1% in both cases) for the HML factor. Industrial portfolio has a positive premium for the same factor (slope coefficients of 0.58 and 0.49 in FF3 and FF5, significant at 1%), but SP500 portfolio value factor is negligible.

Adding investment and profitability to the three-factor model does not modify the coefficients of the market, size, and value variables. The profitability component has a surprising negative coefficient for the SM portfolio (slope of –0.38, significant at 1%), a positive and statistically significant coefficient for the industrial portfolio (0.23), and an insignificant coefficient for the SP500 portfolio. The investment component is not statistically significant for the SM portfolio but has positive premia for the industrial and SP500 portfolios, suggesting conservative investment strategies.

The five-factor model explains return premia on the three portfolios better than the three-factor model and the CAPM – see Table 9. Size, value, profitability, and investment premia are detected for the three investments, with different signs. Smart manufacturing portfolio has the biggest improvement, with adjusted R-squared increasing from 37.8% in the one-factor model to 46.5% for FF3 and 47.3% for FF5. Thus, FF5 better describes smart manufacturing portfolio returns. Table 9 suggests that the FF5 framework improves explanatory power over the three-factor model marginally for all portfolios. Additionally, the five-factor model captures less of average returns on the SM portfolio (47.3%) than on the industrial (88.8%) and SP500 portfolios (96.9%).

Table 9. Model comparison for the smart manufacturing portfolio

Model	Adjusted-R squared	AIC	BIC
Smart manufacturing portfolio (SFTRY.PA)			
One-factor (CAPM)	0.378	2533	2547
Three-factor (FF3)	0.465	2417	2441
Five-factor (FF5)	0.473	2407	2439
Industrial portfolio (XLI)			
One-factor (CAPM)	0.802	1743	1757
Three-factor (FF3)	0.882	1356	1379
Five-factor (FF5)	0.888	1335	1368
SP500 portfolio (SPY)			
One-factor (CAPM)	0.926	833	847
Three-factor (FF3)	0.968	196	219
Five-factor (FF5)	0.969	184	216

4. Discussion

Industrial investments allow capital holders to have exposure to specific, interrelated sectors that closely match market fundamentals and real economic activity. Smart manufacturing is an example of a sector that is forward-thinking, inventive, technologically focused, and concentrated on small enterprises with strong growth and disruptive potential. In this context, understanding pricing determinants is essential for encouraging smart manufacturing investments and improving their risk-adjusted performance.

On this background, this paper builds on previous evidence that increased average returns linked to FF5 have been consistent over time and widespread across markets. Thus, to serve its purpose, the returns of a smart manufacturing portfolio (i.e., the Amundi Smart Factory ETF), which includes 272 smart factories in 30 countries engaged in either Advanced Robotics, Cloud & Big Data, Cyber Security, Augmented Reality & 3D Printing, or the Internet of Things (IoT), are deconstructed by the traditional one-factor, three-factor, and five-factor asset pricing models.

The results for the FF5 model reveal positive loading for the size factor and negative loading for the value and profitability factors, which are statistically significant at conventional levels. This most likely reflects the characteristics of Industry 4.0 companies, many in early growth stages and/or undergoing significant digital transformation processes, as smart manufacturing firms prioritize substantial capital investments in advanced technologies over short-term profitability optimization (Arcidiacono & Schupp, 2024). This strategic approach follows the pattern observed in other technology-intensive sectors where current earnings may not adequately capture the potential of future value creation (Toroslu et al., 2023). Additionally, the Amundi Smart Factory portfolio includes numerous companies that are more technology enablers rather than traditional manufacturers, therefore operating under business models that emphasize less short-term profitability. However, as digital transformation investments will mature and become a source of operational efficiency, we anticipate the profitability factor loading will enter positive territory, aligning with the expectation that smart manufacturing will eventually deliver superior risk-adjusted returns. At the same time, the results deviate from the findings of Fama and French (2015), who find that the value factor becomes redundant in the presence of profitability and investment factors.

For the SM portfolio, the five-factor model explains less than half of the funds' daily variation in returns. These findings are in line with Fama and French (2015), showing the lower power of the FF5 when it comes to capturing average returns on portfolios that exhibit large negative coefficients for profitability and investment factors, i.e., "...that invest a lot despite low profitability". In turn, for the industrial and SP500 tracking funds, the five-factor model leaves little of the daily variation in returns unexplained, while the intercept is statistically zero. The industrial fund has a negative loading for the size factor and positive loadings for the value, profitability, and investment factors, indicating that these are larger stocks with robust profitability and a conservative investment approach. These findings further enforce the belief that small companies are favored by the fourth industrial revolution due to their ability to quickly adapt to market conditions and demand by producing and fulfilling highly customizable orders (Moeuf et al., 2018).

It should be acknowledged that the smart manufacturing portfolio, despite underperforming the SP500 and the conventional industry portfolio when considering the Sharpe and Sortino ratios, is revealed to be consistently less risky than the industrial portfolio and similar in risk to the SP500 tracking portfolio. Moreover, it outperforms both in terms of risk-adjusted performance when adjusting the Sharpe ratio for the expected shortfall. This is a good indicator for investors seeking to reduce the exposure risk of their portfolio, and it would seem likely that the SM fund can fill a similar role to a green fund (Silva & Cortez, 2016) as a safeguard against market volatility.

Presenting the lowest impact of the market risk premium, the SM portfolio insulates better against market risk than the market benchmark and the industry alternative. Through its resemblance to other "responsible" investments, the smart portfolio may inherit the quality reducing investment risk during steep market drops as sustainable funds appeared to behave during the COVID-19 pandemic (Fang & Parida, 2022; Morgan Stanley, 2021). The plot of maximum drawdown depicted in Figure 3 reinforces the superior resiliency of the smart manufacturing portfolio compared to the US market (as proxied by the SP500 tracker SPY) and especially to the conventional industry portfolio XLI during the COVID-19 pandemic-induced market crash in early 2020.

Furthermore, different from Fama and French's (1993) assertion, the SM book-to-market value negative coefficient does not equate to increased volatility of the stock return,

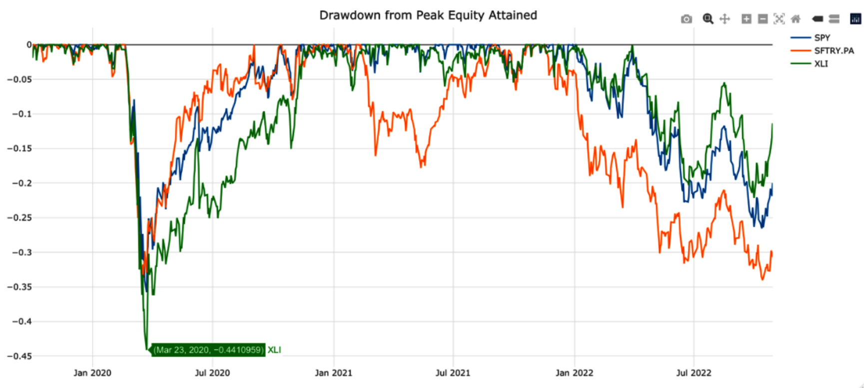

Figure 3. The maximum drawdown for the three portfolios (October 2019 – October 2022)

which is lower than that of the conventional industry portfolio that exhibits a positive exposure to the value factor. Small SMEs with an inclination towards growth through technologization and digitalization seem to be the most likely candidates to succeed throughout the fourth industrial revolution, as the mechanism of a market dominated by smart cyber-physical systems moves in their favor and is opposed to the market mechanism of conventional industry.

Results indicate that the FF5 model appears to yield, if only marginally, better results than the CAPM and the FF3 model. In comparison to the Sarwar et al. (2018) method, which returned far higher coefficients of determination for the high-tech and manufacturing sectors, our model appears to reveal a similar increase in explanatory power when moving from FF3 to FF5 for smart manufacturing, confirming that FF5 is a better alternative for technology stocks than FF3. The dilemma arises when looking at the R-squared values of the smart manufacturing ETF compared to industry and the US market benchmarks. Despite previous research showing that the performance of technology-focused assets can be deconstructed with the FF5, when applied to our SM portfolio, it fails to account for more than half of the variation in returns, despite the very high tilt of the SM portfolio toward information technology firms (71.94%). This is consistent for both CAPM and FF3 and could possibly indicate that rapid advancements in technology, which represent one of the main unknowns in forecasting the performance of a company (Benaroch & Kauffman, 1999), require multifactor models specifically made to account for the type and level of technology involved. Hence, besides market premium, size, valuation, and profitability, there are also other factors that drive the returns of the smart manufacturers' stocks that remain undetected.

5. Conclusions

This paper compares the investment potential of smart manufacturing with those of traditional industrial portfolios, offering capital holders a fundamentals-driven understanding of the advantages of investing in Industry 4.0. Moreover, the study identifies unique risk factors that may affect the returns of smart-manufacturing enterprises, which facilitates the understanding of Industry 4.0. This comparative framework reveals the distinct interactions between risk factors and the expected returns of smart, conventional, and US market portfolios, while also enhancing the asset pricing literature with novel findings.

The main contribution of the study resides in the use of established financial models to analyze smart manufacturing investments, as very few studies have examined the relevance of these specific types of investments for the risk-adjusted return of portfolios. Therefore, our work uniquely bridges cutting-edge manufacturing technology and financial markets, showing that smart manufacturing investments differ from traditional industrial stocks and help diversify portfolios along with providing better protection during economic downturns. Additionally, the Amundi Smart Factory ETF used in our analysis serves as an excellent representative of trends in the Industry 4.0, including 272 companies from 30 countries and considering five core digital technology pillars. The global diversification and integration of multiple technologies reflect the complex nature of smart manufacturing transformation, while the current investment-intensive phase of smart manufacturing adoption is captured by the size and profitability factors loadings. From this perspective, our findings are insightful in understanding the financial implications of Industry 4.0's transformation of global manufacturing.

Our analysis identifies distinct features of smart manufacturing and conventional industrial portfolios during the period under investigation (October 2019–October 2022). First, investors benefit from diversification due to the smart manufacturing portfolio's lower return and risk than the standard industrial portfolio. The size factor is negative throughout the period (small firms fail to outperform big firms), but all other factors have positive premiums, indicating an abnormal market excess return and the relative outperformance of value-oriented, profitable firms with conservative investment strategies. Though smart manufacturing has lower market exposure, all portfolios correlate positively with market risk. Positive size factor loading and negative value and profitability factors suggest that smart manufacturing stocks are smaller, growth-oriented enterprises with high price-to-book ratios and lower profitability. However, the industrial portfolio comprises larger, value-oriented businesses with strong profitability and conservative investment strategies, as evidenced by negative size factor loading and positive value, profitability, and investment factors. These contrasting factor exposures highlight smart manufacturing investments' diversification benefits.

Our findings give investors, portfolio managers, and policymakers the tools to make smarter decisions about incorporating smart manufacturing into their strategies – combining the best of both technological innovation and sound financial analysis. There is a niche for smart-manufacturing activities in equity markets, implying that they can attract investment and allocate resources towards developing new digital technologies that are more efficient, unlock new product creation capabilities and generate fewer pollutants. As Industry 4.0 moves into the mainstream, the performance of smart manufacturing portfolios would also increase with improvements in the profitability of smart factories that embrace the Internet of Things (IoT) and Industry 4.0. Consequently, as investments in smart manufacturing technologies that lead to improved efficiency and quality start to pay off in terms of profitability, smart manufacturing stocks and portfolios will see excess returns as their loading to the profitability factor turns positive, possibly providing in the near-future more than just a digital-focused alternative to sustainable investments, but a reliable diversification tool.

The findings offer significant practical value for multiple stakeholder groups, as their implications extend beyond traditional investment analysis. For investors and portfolio managers, these results provide guidance for capital allocation strategies, advising for more informed decisions about the inclusion of smart manufacturing investments in diversified portfolios. Moreover, the lower systematic risk of these investments supports their role as hedging tools during times of increased volatility and market downturns. Corporate finance teams in smart manufacturing firms can also gain valuable insights from our findings for the estimation of cost of equity and cost of capital, therefore assisting in more accurate valuations and assessment of investment opportunities. Furthermore, risk management teams may use our approach to better assess firms' exposure to technology and support the financing strategy of firms.

Policymakers and regulators can benefit from our results to design and implement more effective industrial and innovation policies. Specifically, specialized investment guidelines that recognize smart manufacturing risk-return profile can be developed, and policymakers may create investment vehicles that capitalize on the diversification benefits of these investments. Moreover, organizations involved in supporting economic development can target resources toward sectors that demonstrate, as smart manufacturing, both technological advancement and resilience. Additionally, for academics, results reveal that despite performing better than the CAPM and the FF3, variations in smart firms' stock returns remain largely unexplained by the FF5. Consequently, it shows that future efforts of developing multi-factor models that can keep up with the pace of technology and explain the returns of stocks of Industry 4.0 companies are needed.

As any empirical work, this research has limits imposed by data availability, the period under scrutiny and the employed model, in our case FF5. Since FF5's key drawback is estimating small business stock returns accurately, future research may overcome these constraints. Thus, it may examine additional smart manufacturing returns-controlling aspects. Further research can also distinguish smart enterprises by country and/or Industry 4.0 supporting technologies. Another interesting research topic is comparing green and Industry 4.0 portfolios or examining how sustainability affects smart manufacturing company profitability.

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Author contributions

C. D. T. and R. S. conceived the study and were responsible for the design and development of the data analysis. AH was responsible for data collection. C. D. T. was responsible for data analysis. A. H., Z. D., L. B., and R. S. were responsible for data interpretation. C. D. T., A. H., and Z. D. wrote the first draft of the article. L. B. and R. S. revised the first draft. All authors contributed to the final version of the article and approved it.

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Authors declare no competing financial, professional, or personal interests from other parties.

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