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Companies intangibles: Unique versus generic

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ABSTRACT

Purpose: In the era of the knowledge economy intangibles are recognized by investors as pivotal value drivers. This paper proposes an intangibles-based tool for picking companies with value growth potential.
Design/methodology/approach: We suggest a model to select companies that effectively use unique intangibles (in contrast to the generic intangibles). To test whether these results can be explained by skill we implement a bootstrap procedure. Companies that are able to use unique intangibles efficiently are combined in a portfolio.
Findings: Only 22% of companies have the skills to use unique intangibles, but all of them are characterized by the efficiency of their use. The created portfolio demonstrates a higher cumulative return, Sharpe ratio and lower drawdown than S & P500. We also find the increasing importance of intangibles for investors during the crisis.
Research limitations/implications: Both the created portfolio and the benchmark (S & P 500 index) are analyzed without transaction costs. Also the benchmark construction is based on equal-weighted sum of company M/B ratios.
Originality/value: We take into account the quality of intangibles (efficiency of unique intangibles use) while previous research of portfolio forming methods is based on quantity of intangibles.

1. Introduction

The primary goal of a typical long-term investor is to pick a company with value growth potential. Because tangible assets cannot fully explain market value, researchers focus on intangible assets. Intangible assets are regarded as key resources that contribute to competitive advantages and enhance tangible assets (Edvinsson, 1997; Sveiby, 1997). The growing awareness of the importance of intangibles for value creation has resulted in an increase in intangibles-related investments. However, investors lack information about the outcomes of such investments when forming portfolios. This lack of information complicates the analysis of the value created by intangibles and therefore the process of picking companies. Also, a company's high current value does not necessarily imply its future growth. Long-term investors are interested in companies with value growth potential. Therefore, they need a tool to determine value growth potential on the basis of present performance and both tangible and intangible resources.

This paper therefore proposes an intangibles-based tool for picking companies with value growth potential. We test the validity of the proposed tool on the sample of US companies included in the S & P500 index. First, we distinguish two types of intangibles according to their uniqueness. We define company resources that are commonly used in an industry as generic intangibles. For example, all employees are trained to work with newly purchased manufacturing equipment. Commonly used new software that simplifies information diffusion between company divisions is another example of a generic intangible resource. We define company resources that are not commonly used in an industry as unique intangibles. For example, a company with a research center that

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patents new technology to reduce production costs produces a unique intangible asset. Reduced costs lead to value enhancement, which raises a company's investment attractiveness. Both generic and unique resources can be used efficiently or inefficiently. Second, we propose a way to measure the efficiency of generic and unique intangibles. We create this measure by comparing the efficiencies of the market and company portfolios of intangibles. Finally, we investigate whether the ability to use unique intangibles is random. The proposed tool combines all three of these steps.

Investment in companies with both generic and unique intangibles can be profitable. However, we suppose that the value of companies that rely mostly on generic resources have a strong correlation with market movements. Thus, we expect that commonly attainable knowledge does not create superior value. Consequently, the ability to produce long-term value is closely connected with the efficient use of unique intangibles. Our proposed model of efficiency of unique-generic intangibles (EUGIn) extends existing tools that pick companies based on tangible assets analyses and assumes the importance of the efficient use of unique and generic intangibles in relation to value creation.

The results of our analyses show the validity of the EUGIn model and its ability to pick shares with better future performance than the benchmark. The median S & P500 company has a negative efficiency for unique intangibles, and the total number of investment-attractive companies is small (22% of the sample). Nevertheless, the success of companies with a positive efficiency for unique intangibles is nonrandom. We also corroborate the importance of unique resources during the economic recession.

The remainder of this paper proceeds as follows. Section 2 introduces the nature of intangibles and their connection with stock markets. Section 3 discusses the theoretical framework of the EUGIn model. Section 4 describes the data and econometrical method that we use to prove the validity of the model. Section 5 presents and discusses the empirical results. Section 6 concludes with summation and discussion of the main results.

2. Theoretical background

A growing body of literature is dedicated to the definition, description, and measurement of intangibles as well as their influence on company results. Of this vast field of literature, we only consider the stream of intangible research connected with capital markets. This section contains a discussion of the term *intangibles* as used in the paper and a critical analysis of the previous research dedicated to the connection between intangibles and capital markets.

Intangibles have vague nature and heterogeneous structure. Therefore, the literature does not provide a single definition (Zambon, 2004; Clarke et al., 2011). The common practice is to interpret intangibles according to the research purpose. Herein we define intangibles according to the value approach, which appeared at the end of the twentieth century upon the integration of the value-based management concept with the intellectual capital framework. Stewart (1997) defines intangibles as intellectual material that consists of knowledge, experience, and intellectual property, which creates value. Edvinsson and Malone (1997) define intangibles as knowledge that can be transformed into value. Zeghal and Maaloul (2010) define intangibles more precisely as all the knowledge that a company uses in value-added creation. Kristandl and Bontis (2007, p. 1518), who provide one of the most comprehensive definitions, describe intangibles as "strategic firm resources that enable an organization to create sustainable value, but are not available to a large number of firms." These resources are non-physical, non-financial, and are not included in financial statements. Some studies use the terms *intangibles* and *intellectual capital* as synonyms. However, we distinguish their meanings. According to our use, intangibles are connected with the nature of the phenomenon whereas intellectual capital is related to managerial and accounting issues. Therefore, because we investigate the intangible-based potential of value growth of companies, we solely use the term *intangibles*.

Ellis and Jarboe (2010) describe models of financing for companies with intangibles. They find that investment funds and banks take intangibles into account when making financial decisions, but current investment methods need substantial improvement. They argue that intangible-based investing requires better methods of intangible valuation. However, although the authors underline importance of intangibles, they consider them from a theoretical viewpoint.

Jagannathan and Wang (1996) modify a capital asset pricing model (CAPM) to include human capital. They demonstrate that the inclusion of human capital explains cross-sectional differences in average returns in contrast to the classic CAPM. They measure human capital returns using the growth rate of the average employee salary as a proxy. This indicator underlines the importance of intangibles in explaining the return on shares; however, intangibles consist of many elements, which we suppose theoretically all transform into share returns. Therefore, although the results of Jagannathan and Wang's research are of great importance, their research idea should be expanded.

Lev and Sougiannis (1999), Chan, Lakonishok and Sougiannis (2001), Chambers, Jennings, and Thompson (2002), and Anagnostopoulou and Levis (2008) use portfolio comparisons to show the relation between market-to-book (M/B) ratio and research and development (R & D) expenses. Chan et al. also analyzes advertising expenses as a part of a company's intangibles, which influence the return on shares. However, researchers usually ignore the other components of a company's intangibles in the portfolio formation process.

In summarizing the literature, we highlight the main drawbacks of prior research dedicated to the connection between intangibles and capital markets. As previously noted, existing studies usually focus on one component of intangibles, such as human capital or R & D expenses. Intangibles are complex and extremely heterogeneous. All of their components can influence a company's outcomes and should be taken into account in the investment decision-making process. However, intangibles are non-physical and non-financial in nature, and therefore their measurement is complicated (Kristandl and Bontis, 2005). An extensive body of literature analyzes the involvement of intangibles in the functioning of a company. This research commonly avoids the measurement of intangibles, however, and instead uses more valid indicators usually connected with value-added indicators (e.g., economic value added or a value-added intellectual coefficient) or market value (M/B, market value added, or Tobin's Q). Although we discuss intangibles from a capital markets perspective, we choose a market value-based method.

Zeghal and Maaloul (2010), Orens, Aerts, and Lybaert (2009), and Youndt, Subramaniam, and Snell (2004) show that the M/B ratio of companies in developed countries has a robust positive relation with proxy indicators of intangibles. Edvinsson and Malone (1997), Stewart (1997), Sveiby (1997), Bharadwaj, Bharadwaj, and Konsynski (1999), and Nold (2012) show that M/B can be used as an approximate measure of intellectual capital and the results of intangibles use. They argue that the higher the M/B coefficient is, the more intangibles a company has and, consequently, the more created value can be explained by the influence of intangible resources. Generally speaking, M/B reflects intangibles creation based on investor expectations (Wu, 2008).

According to Brennan and Connell (2000), the coefficient has at least two weaknesses. First, the spread between market and book value usually cannot be explained only by the influence of intangibles due to the limitations of accounting standards and market inefficiencies. Only the differences between refined book values and market values can be attributed to intangibles efficiency. Second, the coefficient does not give any information about efficiency of intangible use. However, because all intangibles proxies have limitations and M/B ratio is successfully applied in prior empirical research, we argue that its use is feasible under certain restrictive assumptions.

According to the previous discussion, M/B ratio reflects the effectiveness of intangible implementation. Investors often use M/B or its inverse, book-to-market (B/M) ratio, to select investment goals (e.g. Goyal & Welch, 2008; Lewellen, 2004; Campbell & Thompson, 2008). Fama and French (1992) lay the foundation for the use of B/M ratio in finance by showing that B/M coefficients explain cross-sectional variation in stock returns. Since then, a growing body of literature verifies the relation between B/M ratio and stock returns. For example, Kothari and Shanken (1997) and Pontiff and Schall (1998) find that the B/M of the Dow-Jones Industrial Average predicts market returns. Fama and French (1998) show that stocks characterized by a high B/M ratio (i.e., a low M/B) have higher returns in the future. In addition, they find support for this result in different capital markets. Johnson and Soenen (2003) analyze B/M influence on the other performance indicators and show that companies with a high B/M have a higher Jensen's α, a higher share of economic value added in material assets, and a lower Sharpe coefficient. Therefore, M/B coefficient negatively relates to future share returns.

Given this discussion, we conclude that M/B is an indicator of the results of intangible use and predicts future share returns. We therefore confirm its validity as an acceptable coefficient for this study. Prior research dedicated to the analysis of intangibles usually considers the quantity of the available indicator (e.g., wage per employee, R & D, advertising expenses, etc.). We argue that a more essential feature is quality, in other words, the ability to create value. In this case, M/B is most suited to our research purposes.

3. EUGIn model

We develop the EUGIn model, which can be used to choose investments on the basis of unique intangibles efficiency. However, we first outline the following main assumptions. First, the financial markets have semi-strong form efficiency. This assumption implies that all public information is calculated into a stock's current share price (Fama, 1970). All speculations are excluded from the analyses. Second, book value is approximately equal to the cost of replacement. Company assets are revaluated at current prices. Third, M/B ratio reflects the effectiveness of intangibles implementation. Consequently, the spread between market and book value represents the part of a company's value that is attributed to intangibles efficiency. Fourth, intangibles are heterogeneous. Although a variety of intangibles classifications exist, we classify intangibles as generic and unique. Fifth, M/B ratio quickly reacts to changes in systematic innovativeness. In other words, M/B reflects all public information about innovations. Companies that do not innovate or buy unique resources use generic resources. Finally, companies that use unique intangibles efficiently are more attractive to investors than companies that use commonly available knowledge from the market (i.e., generic intangibles).

We calculate M/B as the ratio of company's market value (M) to book value (B). Market value consists of book value and a spread, referred to as market value added (MVA):

$$\frac{M}{B} = \frac{B + MVA}{B} = 1 + \frac{MVA}{B} \tag{1}$$

According to the literature (e.g., Pulić, 2000), MVA reflects the results of intangibles use. We divided that result into the effect of unique and generic intangibles use based on our fourth assumption:

$$\frac{M}{B} = 1 + \frac{MVA}{B} = 1 + \frac{MVA_U + MVA_G}{B} \tag{2}$$

where $MVA_U(MVA_G)$is the part of a company's MVA generated by unique (generic) intangibles. Generic resources are widely used in the market, and thus MVA_G is closely connected with market movements. So we write

$$\frac{MVA_G}{B} = \beta\cdot\left(\frac{MVA}{B}\right)_m \tag{3}$$

where $(\frac{MVA}{B})_m$ is the ratio of market value added to book value of a market, and β is the elasticity of company intangibles efficiency to market intangibles efficiency. Eq. (3) can also be written as the coefficient of simple linear regression (Eq. 6) or, in other words, as

$$\beta = \frac{cov\left[\left(\frac{M}{B}\right)_i;\left(\frac{MVA}{B}\right)_m\right]}{\sigma_m^2} \tag{4}$$

where $\left(\frac{M}{B}\right)_i$ is the ratio of market value to book value of a company, and σ_m^2 is the variance of $\left(\frac{MVA}{B}\right)_m$.

The coefficient β reflects generic intangibles efficiency and can take three different values. $\beta \in (-\infty; 0)$ suggests a negative connection between a company and a market portfolio of intangibles based on their efficiencies. That is, a company and the market have common intangible resources; however, their use of these intangibles differs. The company uses commonly available intangibles inefficiently that are implemented successfully by the market as a whole, or vice versa. Thus, in case of $\beta \in (-\infty; 0)$, the use of generic intangibles destroys company market value. When $\beta \in (0; 1)$, a company's efficiency of intangibles has a positive but weak connection with market efficiency. $\beta \in (1; +\infty)$ suggests that a company's M/B ratio is increasing faster than the market's M/B ratios. The company successfully uses generic intangibles, and its value has a strong connection with market movements.

$\frac{MVA_U}{B}$ is unconnected with market fluctuations. Therefore, we find it through the estimation of the intercept of regression Eq. (4) and denote it as α. It shows that a company performs better (or worse) than expected by its correlation with market intangibles efficiency. In other worlds, α shows the difference in efficiency between the observed company and a company that use only generic intangibles. Statistically, this coefficient reflects intangibles efficiency that cannot be explained by market movements connected with knowledge use.

When $\alpha < 0$, a company's unique intangibles are used inefficiently. The company differs from the market, but if the company does not have unique resources (i.e., if the company only uses generic intangibles), it would have a larger M/B ratio. This result can be explained by a combination of large investments and low effect. When $\alpha > 0$, a company uses unique intangibles effectively to create value. In other words, a company's M/B ratio is larger than the M/B ratio of a company with the same β (efficiency of generic resources). This company has the ability to create value by efficient use of unique intangibles.

We write the following equation for the ordinary least squares estimation:

$$\left(\frac{M}{B}\right)_i = (1+\alpha) + \beta_i \cdot \left(\left(\frac{M}{B}\right)_m - 1\right) \tag{6}$$

A company's M/B ratio has a knowledge-free part equal to 1. This part is assumed to be the M/B ratio of company that uses intangibles in such a way that they do not create any value, and investors estimate its market value equal to its book value.

We highlight two features of the proposed model. First, we do not regard generic and unique resources as substitutes. A company may have both types of resources. Coefficients α and β allow us to evaluate their efficiencies separately. Second, both types of resources can be created inside or be purchased from outside a company. Third, the term *unique* does not imply the absolute uniqueness, and *generic* does not imply that all of the market companies have the resource. Both terms are relative. If a company does not have a covariance with the market, we conclude that it has unique resources, but we cannot measure the level of uniqueness or the quantity of such resources because we analyze only their results.

Although the form of the EUGIn model is similar to the CAPM, they are distinct in several key ways. First, we concentrate on intangibles analysis. Our aim is to determine company differences in value creation on the base of intangibles. We choose M/B value to measure the results of value creation because it is commonly used in similar research. CAPM explains cross-sectional differences in share returns. Second, the ability of the EUGIn model to pick investment goals in the stock market is only one possible application of this method. It can also be used for benchmarking companies by their application of intangibles or to analyze company development.

We suppose that companies with high α are the most attractive investment goals. They are able to buy or create unique intangibles and effectively implement them. This assumption is checked in the following sections.

4. Data description

4.1. Initial sample

We examine monthly M/B ratio and stock prices from the Center for Research in Security Prices (CRSP) data for US companies in the S & P500. The sample period is from January 2000 to January 2012. We justify the choice of US companies based on the important role of intangibles in the United States, according to the Knowledge Economy Index of the World Bank and the National Intellectual Capital Model (Yeh-Yun Lin and Edvinsson, 2008), which estimates the overall level of a country's development and the efficiency of its use of knowledge. We choose S & P500 companies because companies' stocks on this index are more liquid than others (due to index construction methodology). We assume that public information is the main fundamental factor that drives S & P500 stock prices. Further details on M/B ratio and stock prices are available from CRSP.

4.2. Market ratio

We compare all S & P500 companies with a benchmark constructed by calculating an equal-weighted sum of the company's M/B ratios (we exclude all preferred stocks). We use equal weights because it is the best choice in the context of Occam razor principle: no evidence suggests the need for capitalization weighting, so we choose the simplest method.

Table 1
Summary statistics for monthly returns and monthly M/B ratio.

	Returns		M/B	
Date	Mean (%)	*N* obs	Mean	*N* obs
2000	–	–	2.26	5354
2001	0.59	5035	1.62	5992
2002	–1.39	4712	1.40	6090
2003	3.08	5735	1.34	6103
2004	1.54	4817	1.51	6150
2005	1.13	5790	1.53	6168
2006	1.32	5756	1.56	6168
2007	0.59	5719	1.54	6168
2008	–3.37	5712	1.20	6163
2009	3.44	5721	0.97	6168
2010	3.42	4769	1.13	6168
2011	0.05	5721	1.21	5680
2012	5.42	476	1.33	6

Notes: This table contains the mean values for the sample period. Observations reflect monthly data.

4.3. Summary statistics

Table 1 contains summary statistics for the monthly returns and the monthly M/B ratio. This table provides mean values for the sample years of 2000–2012. No clear trend emerges for either returns or M/B ratio. As expected, both returns and M/B ratio decline during the financial crisis (2008–2009). Because no clear trend exist, cross-sectional variation appears more significant than time variation. Even during the crisis period, which is expected to be homogeneous, the returns are similar in absolute values but are of the reverse sign. The correlation between returns and M/B ratio is negative (–19%) but statistically insignificant (t = –0.6243).

5. Methodology

5.1. α Estimation

To evaluate α, we estimate the following equation with ordinary least squares:

$$\left(\frac{M}{B}\right)_i = (1+\alpha) + \beta_i \cdot \left(\left(\frac{M}{B}\right)_m - 1\right) \tag{7}$$

However, the estimation of α estimation is not sufficient. We must prove that high-α companies create value and are attractive to investors (which is the main practical application of our framework). To create a portfolio, we need the dynamics of α. To this end, we use a rolling window of 50 months and estimate 95 (which is the length of the out-of-sample period) α values for each company. We choose the size of window simply to keep the initial subsample estimation period long enough. However, our results are robust for other window sizes; results are available on a request.

Because we use ordinary least squares without IV, we must address the endogeneity problem. At least two reasons for endogeneity may bias the estimates: the interdependence between M/B value of the benchmark and a company and a missing variable affecting both sides of the equation. Our benchmark is equal weighted, so the influence of one company on the whole benchmark is minimized, which addresses the first issue. Addressing the second issue, we conclude that systematic innovativeness is a potential source of endogeneity (systematic risk in CAPM estimations is a good analogy). So, the main question is how long does the market M/B ratio, as our benchmark, take to reflect changes in systematic innovativeness (e.g., new discoveries like the Internet that affect the whole market). We therefore suppose that all public innovations are reflected in market M/B ratio.

5.2. Luck vs. skill

After estimating α, we must determine whether α significantly differs from null. To answer this question, we need a proper α inference. In this setting, bootstrapping is necessary for proper inference due to the propensity of an individual company to exhibit a non-normally distributed M/B ratio. These non-normalities arise for several reasons. First, the distribution of the M/B ratios may be non-normal. Second, the market ratio may be non-normal, and co-skewness of the market and individual M/B ratios may be obtained. Finally, individual ratios exhibit varying levels of time-series autocorrelation in the M/B ratio. Thus normality may be a poor approximation in practice, even for a fairly large sample. Bootstrapping can substantially improve on this approximation, as Bickel and Freedman (1984) and Hall (1986) show.

We base our bootstrap procedure on the work of Kosowski et al. (2007). For each company i, we draw a sample with a replacement from the residuals, which we save in the first step when estimating companies α and β. Next we create a pseudo time series of the resampled residuals, $\hat{e}^b_{i,t_\varepsilon}$, $t_\varepsilon = s^b_{T_{i0}},\ldots,s^b_{T_{il}}$, where b is an index for the bootstrap resample number and where each of the time indices $s^b_{T_{i0}},\ldots,s^b_{T_{il}}$ are drawn randomly from $T_{i0},\ldots,T_{il}$ in a way that reorders the original sample of $T_{i0}-T_{il}+1$ residuals for company *i*.

Next, we construct a time series for the pseudo M/B ratio for this company, imposing the null hypothesis of zero true performance ($\alpha = 0$ or $\beta = 0$) and taking the benchmark at the same time as residual:

$$\left(\frac{M}{B}\right)^b_{i,t} = 1+\hat{\beta}_i\cdot\left(\left(\frac{M}{B}\right)^m_{t_\varepsilon}-1\right)+\hat{e}^b_{i,t_\varepsilon} \tag{8}$$

where $t{=}T_{i0},\ldots,T_{i1}$ and $t_\varepsilon{=}s^b_{T_{i0}},\ldots,s^b_{T_{i1}}$. As Eq. (4) indicates, the artificial M/B ratio has a true α (or β) that is zero by construction. When we regress this ratio for a given bootstrap sample, *b*, on the market ratio, a positive estimated α (or β) may result, because that bootstrap may have drawn an abnormally high number of positive residuals, or, conversely, a negative α (or β) may result if an abnormally high number of negative residuals are drawn.

Next we repeat the previous steps across all firms $i = 1, \ldots, N$ to describe the cross-section of bootstrapped α (and β). By repeating this procedure for all bootstrap resampling simulations, $b = 1, \ldots, 1000$, we build the distributions of these cross-sectional draws of α and β.

5.3. *Portfolio construction*

As previously discussed, to show the practical implications of the proposed approach, we create a portfolio based on α. We start our portfolio in March 2004 and rebalance it each month according to the following procedure: (i) estimate A of current subsample of $[t - window,\ t]$; (ii) implement the bootstrap procedure to check whether α results from skill (not luck); (iii) choose companies with a positive α and skill; (iv) calculate asset weights of the portfolio as α-weighted; (v) at time $t+1$, the portfolio contains only (iii) companies with (iv) weights; and (vi) next period, go to (i).

The result is the time series of the portfolio, which we subsequently refer to as the EUGIn portfolio. We compare the return and risk of the EUGIn portfolio with the return and risk of the S & P500 index as a commonly accepted benchmark of market performance. We exclude transaction costs, liquidity, and other important details from the discussion. Our main goal is to analyze EUGIn, not to offer a complete trading strategy. Correspondingly, the benchmark of the EUGIn portfolio is the S & P500 index, which does not take into consideration transactions costs either.

6. Empirical results

We use the statistical package R to make all the calculations described in the following discussion. We analyze companies included in S & P500 index for 13 years. The total number of analyzed companies is 514 because the structure of S & P500 changes each year.

We implement the methodology as previously described and obtain α values. Fig. 1 shows their distribution. Table 2 reports the descriptive statistics of α. The mean and median values are negative but close to zero. These findings mean that the majority of companies are not able to use unique resources efficiently, and thus they destroy value. The distribution's long left tail indicates that our sample includes companies with a large negative value of α, which means that unique intangibles can substantially decrease a company's M/B ratio. That is, pursuing unique intangibles is risky; a company that does not follow the market can destroy its value and decrease its M/B.

After evaluating α, we implement the bootstrap procedure and determine whether the α is the result of luck or skill. Fig. 2 shows the indicator of skill (grey line) in the lower portion. The upper portion represents the corresponding value of α that is grouped by the

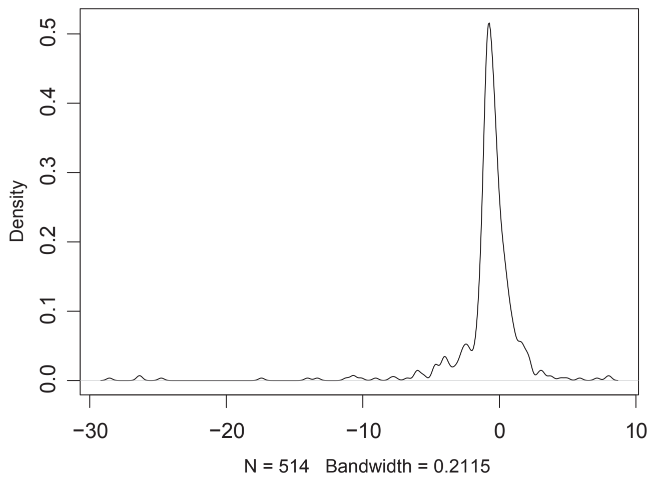

Fig. 1. Distribution of α.

Table 2
Descriptive statistics of α.

	Minimum	1st quantile	Median	Mean	3rd quantile	Maximum
α	–28.56	–1.101	–0.6514	–0.9798	–0.0033	8.041

progressive total (black line). The skill indicator line takes a lower (higher) position if α results from the luck (skill). Importantly, the figure shows that a positive α characterizes all skilled companies (i.e., those that use unique resources efficiently). Thus, a negative α is always the result of chance whereas a positive α is almost always merited. However, a positive α is not always the result of skill; a number of companies (lower right) have a positive α due to the luck.

Finding a close connection between skill and a positive α value can be also corroborated by the correlation analyses. The correlation between α and skill is significantly positive (0.39); t-statistic is 12.79. Therefore the M/B ratio increases in companies that are skilled and efficiently use their unique intangibles. Surprisingly, only 113 companies of our sample (approximately 22%) use unique intangibles efficiently. Although we analyze well-known, stable, and liquid companies, less than one-fourth sustainably create knowledge on the basis of intangibles.

To validate the analysis, we make brief cases studies. A positive α as the result of skill characterizes the most interesting companies. Our examples are Netflix, Inc.; Intuitive Surgical, Inc.; and C. H. Robinson Worldwide, Inc.

Netflix, Inc. is an American provider of on-demand Internet streaming media. It was created in 1997 to organize a DVD-by-mail service during the VHS era. Netflix recognized the potential of DVDs and created a new kind of service. Netflix innovated again to develop video-on-demand services. The company permanently improves the quality of its network capacities through innovation. As a result, approximately 30% of all downloaded US Internet traffic is films and TV shows watched through Netflix's video-on-demand. The Canadian company Sandvine Intelligent Broadcast Networks (2011) argues that Netflix fundamentally changed the Internet market. Therefore, we conclude that the company has a unique idea and efficiently use the intangibles connected with it.

Intuitive Surgical, Inc. is the industry leader in the manufacture of robotic surgical systems. Intuitive Surgical developed and installed nearly 3,000 of its surgical systems, the da Vinci Surgical System, as of July 2013. The company has 1,250 US and foreign patents and more than 1,150 US and foreign patent applications. Thus, it creates unique knowledge as a result of skill implementation.

C.H. Robinson Worldwide, Inc. is a large transportation and logistics company. Unlike Netflix or Intuitive Surgical, it does not depend on unique ideas or patented R & D. Instead, C.H. Robinson Worldwide uses network development and relationships with approximately 56,000 transportation providers worldwide. Developing and maintaining relationships with company stakeholders is a large part of its intangibles. C. H. Robinson Worldwide creates value by building trusting relationships and cooperating with a large number of providers.

Skilled companies that use unique intangibles efficiently, such as the case studies previously discussed, are potentially attractive to investors. Investor expectations are met in market value and measured by return, Sharpe coefficient, Jensen's α, and drawdown, among others. We use three indicators to evaluate the results of investments: mean return, Sharpe ratio, and maximum drawdown. The Sharpe coefficient takes into account both profitability and risks whereas drawdown is a more practice-oriented indicator. Fig. 3 presents the cumulative returns of the analyzed portfolios.

Fig. 3 shows that the cumulative return of the EUGIn portfolio is higher than the S & P500 return for most of the analyzed interval. Another important finding is that the return of the EUGIn portfolio starts to exceed the S & P500 significantly during financial crisis of 2008–2009. The recovery period is also characterized by a higher EUGIn cumulative return. We conclude that skilled companies with

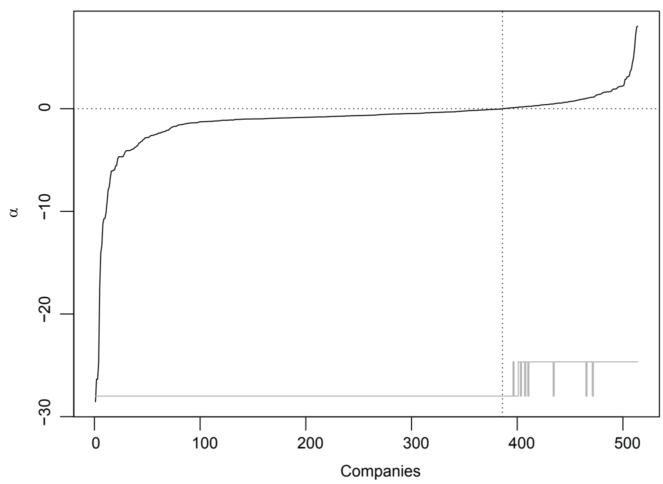

Fig. 2. Skill indicator line (grey line) and the corresponding values of α (black line).

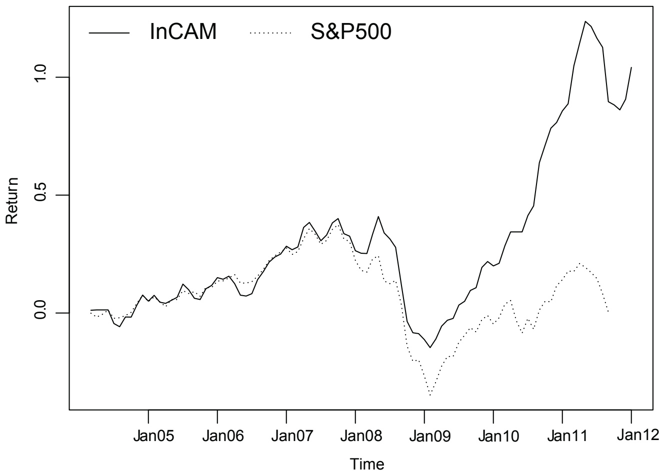

Fig. 3. Cumulative return of EUGIn and S & P500 portfolios.

a positive α perform better during the crisis. Their independence from the market movements allows them to maintain market share, turnover, and, correspondingly, the support of investors.

Table 3 presents the results of portfolio comparisons based on mean return, Sharpe ratio, and maximum drawdown using the algorithm of portfolio construction as previously described. The mean return of the S & P500 is higher than the return of the EUGIn portfolio. However, the EUGIn portfolio has a much lower standard deviation. As a result, the EUGIn portfolio is characterized by a higher Sharpe coefficient. Also, skilled companies with a positive α have lower drawdowns. These results show that the combination of skill and efficient use of unique intangibles allows companies to reduce possible risks. Investors do not evaluate them at a higher rate; therefore, their return is less than the S & P500 portfolio return. However, they considere such companies less risky, especially during the crisis.

7. Conclusions and discussion

The literature review shows that methods of portfolio formation based on intangibles are limited by the analysis of a single component of intangibles, usually human capital, R & D expenses, or advertising costs In addition, prior studies usually only take into account intangibles' quantity (wage per employee, R & D, and advertising expenses, etc.). We argue that a more essential feature of intangibles is their quality, in other words, their ability to create value. Therefore, we propose a method that distinguishes two attributes of intangibles based on their uniqueness: generic and unique resources. Generic intangible resources are widely spread across the market whereas unique resources are much less common. We distinguish these two attributes by comparing a company's portfolio of intangibles and a market portfolio based on their efficiencies.

According to Stewart (1997), Sveiby (1997), and Nold (2012), companies that use intangibles efficiently raise their M/B ratio and, therefore, are attractive to investors. Our proposed EUGIn method predicts which companies have value growth potential on the basis of their ability to use unique intangibles efficiently. To use our model to make investment decisions, we must explicitly control for a potential data-snooping bias: "There is always the possibility that any satisfactory results obtained may simply be due to chance rather than to any merit inherent in the method yielding the results" (White, 2000, p. 1115). We examine the statistical significance of the performance and performance persistence of the best and worst performing companies with a flexible bootstrap procedure applied to the EUGIn. We apply the proposed algorithm to a data set that consists of S & P500 companies and covers the period from 2000 to 2012.

The implementation of the EUGIn model to portfolio formation provides several pivotal findings. First, a small share of the sample represents skilled companies with a positive α. Only 22% of companies possess the skills needed to use unique intangibles efficiently. In fact, companies have a negative median efficiency of unique intangibles. Therefore, even though we analyze well-known, stable, and liquid companies from the S & P500 index, the majority of them are not good investment goals. Their success cannot be explained by the use of unique resources, and their results are highly correlated with market movements.

Second, all skilled companies have a positive α. Negative αs are the result of chance whereas positive αs are mostly merited. Therefore, we hypothesize that investors usually positively evaluate the potential of growth of companies that use unique intangibles

Table 3
Portfolio comparisons.

	Mean return (%)	Standard deviation	Maximum drawdown	Sharpe ratio
EUGIn	5.476	0.0049	0.5513	0.11
S & P500	31.95	0.0438	0.7225	0.073

non-randomly.

Third, portfolio comparisons show the availability and validity of the EUGIn model for picking investments. The EUGIn portfolio demonstrates higher cumulative returns, Sharpe ratio, and a lower drawdown than the S & P500 portfolio. Because the EUGIn portfolio's success is based mainly on reduced risks rather than higher returns, skilled companies are not necessarily more profitable compared to other S & P500 companies. However, they are less volatile, especially during the financial crisis (2008–2009).

Finally, the results underline the increasing importance of intangibles for investors during the crisis. Although exogenous shocks influence both companies that rely on generic resources and those that rely on unique intangibles, those that use unique intangibles efficiently avoid a sharp drop in market value. The idea that company intangibles are of great importance during an economic recession is widespread. This study extends the understanding of the role of intangibles during a crisis by showing that unique intangible resources are more profitable than other intangibles during an economic downturn.

This study has several limitations and shortcomings. The first limitation is the absence of accounting for transaction costs. Both the EUGIn portfolio and the S & P500 index are analyzed without transaction costs. The second shortcoming is the benchmark construction. We use the equal-weighted sum of companies' M/B ratios. The third limitation relates to difficulties associated with α, β, and the luck and skill estimation. Using the EUGIn model requires the use of a bootstrap approach to determine skilled companies. Therefore, the benefits and costs of EUGIn implementation should be measured prior to calculations.

Suggestions for future research are mainly connected with improvements of portfolio comparisons and regression estimation. We offer several opportunities to build on this study. A future study should use a cross-sectional bootstrap method that can deal with cross-sectional correlations in company M/B ratios. The results can also be expanded by taking into account another time period or testing another sample. Portfolio formation in the recovery period may show interesting results. In addition, we test the EUGIn model on a sample of US companies included in S & P500 index. However, the fit of the EUGIn should be tested on other capital markets and for small and medium-sized enterprises. We hypothesize that the results would be worse because the other markets are less perfect and do not reflect investors expectation based on intangibles analysis as well. Future studies should analyze a different portfolio constructed using the EUGIn method. For example, a portfolio can be formed of companies with a positive beta: these companies use generic resources but do so efficiently. Finally, investigate the economic outcomes of the EUGIn by analyzing the economic performance of skilled companies that efficiently use unique and generic resources. Investors likely build their expectations on the base of outputs, not inputs analysis. Relatedly, here we estimate our model according to statistical criteria, but a future study may build a trading strategy based on the EUGIn model and then calculate economic profit, taking risks and the costs of investment into account.

In sum, our research shows the need for differentiating companies' resources according to their uniqueness. A company's α is at least one investment benchmark, but it is necessary to evaluate its persistence. Bootstrapping helps us to reduce but does not eliminate problems with ex post sorts.

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