Nasdaq Data Link Dataset Survey:
Patent Value Estimates [PVE]

Abstract

We investigate a new dataset on patent value estimates. Using constituents of the STOXX Europe 600, we create a patent value factor which is the ratio of each company's patent value to its total assets. We show that a simple dollar-neutral trading strategy where we buy (sell) companies with relatively large (small) patent value factors delivers a Sharpe ratio 50% higher than the underlying index at a confidence $p<0.001$. Our strategy remains performant under a variety of robustness checks over a 13year time horizon, including the 2007 recession and the extreme market turbulence in early 2020. It suggests that the dataset holds information content not currently priced in by the equity market.

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Private and Confidential

1. Introduction

Patents document a company's commitment towards innovation and investing in its own technologies and products. Studies have shown that companies with high-quality patents and strong Intellectual Property (IP) activity have a much better future prognosis than those that invest less in innovation; this improved outlook manifests itself in superior long-term equity returns[1]. In this research note, we will use estimated patent values from the PVE dataset to build an investment factor, IP Alpha, and test if it delivers robust alpha signals in the market.

1.1 Dataset background

The value of a company's patents cannot be found anywhere in the balance sheet (only costs for IP under "intangible assets"); thus, patent values can only be determined using an appropriate patent valuation approach. Our partner has a strong background in intellectual property rights (patents, utility models) and innovation management. They focus on valuation of patents / utility models, patent families and entire corporate portfolios qualitatively and monetarily.

1.2 Research Outline

We derive a new metric called IP Alpha for financial investment purposes by normalizing the estimated patent values by total assets.

Taking IP Alpha as an investment factor, we rank it and construct equal weighted portfolios in several groups based on quantiles. Long-only and long-short trading strategies are implemented using constituents of the STOXX Europe 600. In our backtests, we find that the high (low) IP Alpha portfolio outperforms (underperforms) the benchmark index. Considering the broad coverage of this dataset, we also extend our backtest to include a long-short strategy on a global basket of securities. In each case, our studies yield promising returns over the past 10 years.

[1] i). Hall, Bronwyn H.; Thoma, Grid; Torrisi, Salvatore: The Market Value Of Patents And R&d: Evidence From European Firms; National Bureau Of Economic Research; Cambridge, MA 02138; September 2007
ii). Share of intangible assets on company values; Ocean Tomo, Jan. 2015

2. Backtesting Methodology

2.1 Investment factor: IP Alpha

In order to convert the estimated patent values into a financial factor, we build a factor called Intellectual Property Alpha or "IP Alpha", which is simply the proportion of the patent value in total assets.

$$IP\ Alpha = Estimated\ Patent\ Value\ /\ Total\ Assets$$

2.2 Portfolio Construction and Trading Strategies

In this section, we discuss our portfolio construction methodology and steps taken to design the trading strategies and verify the existence of alpha. Stocks with high (low) IP Alpha are shown to outperform (underperform) the benchmark index and thus, we construct profitable long and long-short strategies.

2.2.1 P~~o~~rtfoli~~o~~ C~~on~~structi~~on~~

Intuitively, if a company with high patent value proportion does indeed have a relatively good future pregnosis, the stocks with high IP Alpha should outperform those with low IP Alpha; we find this to be true, at least in the mid-long run. The way that we construct the portfolios is similar across the trading strategies applied in our backtests:

We order the IP stocks by descending IP Alpha and construct equally weighted portfolios according to their quantile ranking. The intuition here is that companies in the high IP Alpha quantile contain value not yet realized by the market in excess of other lower IP Alpha quantiles and thus, should outperform over the long-term.

2.2.2T~~ra~~ding Strategy

Setup/Assumptions: As PVE is monthly updated with a 2~4 weeks lag, we applied a 1-month lag in our backtesting so that no looking forward bias will be suffered from. No transaction fees are considered.

Portfolio rebalancing: the portfolios in our backtesting are all rebalanced by the end of each month when the data updates are surly available.

Long-only Strategy: using constituents of the STOXX Europe 600, long the high IP stocks and compare the resulting performance to the index as a benchmark.

Long-short Strategy: using constituents of the STOXX Europe 600, long (short) the high (low) IP stocks and compare the resulting relative performance with different each cutoffs.

2.3 Stock Universe

The backtest on the STOXX Europe 600 starts with the first data point in PVE, on 2007-01-31. Once the delivery lag is incorporated, trading performance starts on 2007-02-28 and ends on 2020-05-31, our backtesting period covers the 2007 recession and the recent market turbulence in early 2020. . Not all companies own patent values primarily depending on the industry, PVE covers ~80% of the index constituents which do have registered patents, we call it as select STOXX which will be serving as the stoxx universe in the following backtesting.

4. Backtesting Performance

4.1 STOXX Europe 600: Long-only

In this section, we will implement both long-only and long-short trading strategies on STOXX Europe 600. Our data universe, we refer to as select STOXX, covers the index components having estimated patent values in PVE dataset. All portfolios are equally weighted and rebalanced by the end of each month

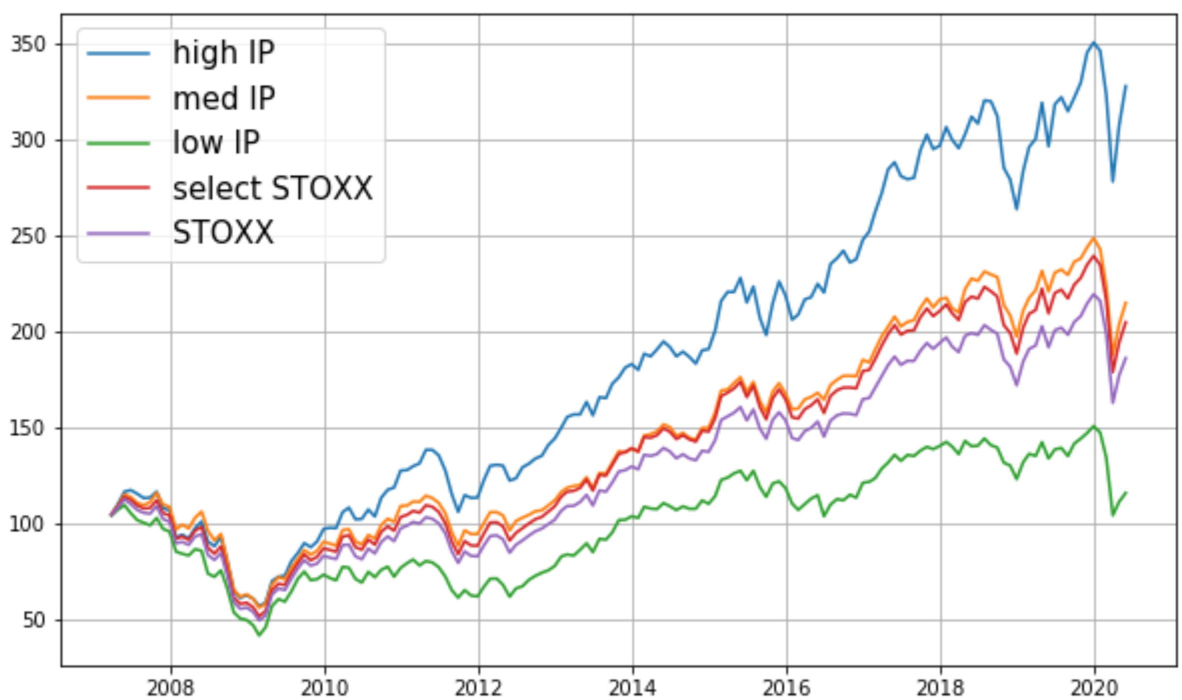
Besides providing the portfolio performance, our research investigated sector and market cap bias, we also discussed factor sensitivity by constructing portfolios with different quintile cutoffs.

a. Summary

We split the IP stocks into three portfolios according to the IP alpha ranking: the top 30% as the high IP, the bottom 30% as the low IP, and the remaining 40% as the med IP. The chart below (Figure 1) clearly demonstrates that higher (lower) IP alpha portfolios yield relatively higher (lower) returns.

Figure 1: STOXX Europe 600 in Three Baskets

Period: from 2007-02-28 to 2020-05-31



We choose the high IP portfolio as the baseline portfolio for our analysis. Table 1 provides an overview of its performance compared to the total market. Select STOXX contains all the index components with patent values estimates; STOXX contains all index components. We construct IP portfolios by ranking IP alpha and thus, stocks without patent values are not considered. As a result, select STOXX is viewed as a more comparable benchmark.

IP alpha delivers alpha in different aspects: higher annualized mean return and similar level of risks, both contributing to the sharpe ratio; the returns of the high IP portfolio are also significantly greater than the select index.

It is worth mentioning that the relative value of the Sharpe ratio is much more meaningful than the absolute value in this case. If we look at the Sharpe ratio of the market, STOXX Europe 600, it tends to be low in monthly frequency, this is because Sharpe ratio can be artificially increased by trading more frequently. As we can see in Table 1, both of the select STOXX, serving as the benchmark, and the constructed portfolio with high IP outperform the market. The high IP portfolio also has a significantly higher Sharpe ratio compared to its benchmark, indicating the existence of alpha.

Table 1: High IP Portfolio vs.. Total Market trading with Long-only Strategy

	Long (top 30%)	**Select STOXX**	**STOXX**
Annualized mean Return	**10.6%**	6.98%	6.23%
Annualized SD of Return	**0.17**	0.17	0.17
Sharpe Ratio	**0.61**	0.41	0.36
Companies in Universe	**281**	830	1,079
Observations	**22,471**	74,848	96,738
Significance*	**0.001**	-	-

* Compared the high IP portfolio to Select STOXX and STOXX respectively here, both t-test significance are <0.001. The performance of the high IP portfolio is significantly higher to both benchmarks.

b. Bias

IP alpha may perform differently across sectors and different sizes of market capitalization. In this section, we will investigate performance sliced by sector and market cap.

i. Sector

The baseline strategy includes all stocks found in the PVE dataset; however, companies in certain sectors choose to invest more heavily in intellectual property than others, such as the sectors of IT, Health Care, Industrials, and Materials. Table 2 below shows the independent performance of each sector.

It is undeniable that PVE has intrinsic bias to certain sectors such as materials, health care, IT, and industrials, but if we look at the breakdown of the baseline portfolio shown in Table 2, we can see the heavier-weighted sectors are not having significantly higher returns compared to the baseline portfolio. This suggests that the intrinsic sector bias in PVE dataset is not the essential alpha source in the baseline.

Table 2: Baseline Portfolio Performance Decomposed by Sector

Sector*:	**MA**	**CD**	**HC**	**IT**	**IN**	**CS**	**BL**
Annualized Mean Return	9.5%	10.4%	11.6%	12.4%	9.5%	10.5%	**10.6%**
Annualized SD of Return	0.2	0.22	0.13	0.22	0.19	0.14	**0.17**
Sharpe Ratio	0.46	0.47	0.89	0.56	0.49	0.73	**0.61**
Observations (% in baseline) (% in select STOXX)	3,734 (17%) (11%)	2,313 (10%) (11%)	4,523 (20%) (8%)	2,620 (12%) (6%)	7,046 (31%) (23%)	1,090 (5%) (8%)	**22,471**
Significance**	0.73	0.47	0.12	0.26	0.81	0.48	**0.001**

Sector*:	EN	COM	FI	UT	RE	BL
Annualized Mean Return	- 1.03%	5.0%	22.2%	42.9%	32.0	**10.6%**
Annualized SD of Return	0.31	0.22	0.36	0.622	0.3	**0.17**
Sharpe Ratio	-0.03	0.22	0.58	0.69	1.01	**0.61**
Observations (% in baseline) (% in select STOXX)	494 (2%) (6%)	401 (2%) (8%)	144 (1%) (13%)	94 (0.0%) (5%)	12 (0%) (1%)	**22,471**
Significance**	0.98	0.88	0.19	0.07	0.4	**0.001**

***** GICS sectors: Materials (MA), Consumer discretionary (CD), Health care (HC), Information technology (IT), Industrials (IN), Consumer staples (CS), Energy (EN), Communication Services (COM), Financials (FI), Utilities (UT), Real estate (RE), and Baseline (BL).
** Paired one-sided t-test between the sector portfolio returns and baseline returns.
Note: The baseline portfolio does not include Real estate (RE) stocks.

ii. Market Cap

Table 3 below shows the performance when we split the baseline portfolio into different market cap sizes. The cap size structure is very similar to the benchmark, indicating the market cap bias is negligible. Moreover, large-cap contributes the most to the baseline performance.

Table 3: Baseline Portfolio Decomposed by Market Cap

Market Cap (EUR):	small-cap < 1B	mid-cap 1-10B	large-cap > 10B	All (baseline)
Annualized Mean Return	-18.4%	9.8%	13.7%	**10.6%**
Annualized SD of Return	0.32	0.2	0.15	**0.17**
Sharpe Ratio	-0.58	0.50	0.91	**0.61**

Observations (% in baseline) (% in select STOXX)	1,109 (5%) (7%)	11,225 (50%) (51%)	10,137 (45%) (42%)	**22,471**
Significance*	0.99	0.80	0.006	**0.001**

* Paired one-sided t-test between the monthly returns of small-, mid-, or large-cap portfolio and the baseline.

c. Quantile Cutoffs Analysis

The baseline strategy longs the top 30% of IP value stocks. The table below shows the long-only performance when we use different quantile cutoffs.

When the cutoff goes higher, the performance of high IP portfolio is not necessarily improved. When the sample size is too small, it will be noisier and starts to dilute the factor alpha. Overall, the relationship between the high IP performance and the quantile cutoff is concave, the turning point can be found out by empirical data. In terms of the STOXX Europe 600, the optimal cut-off is around 30%.

Table 4: Long High IP stocks with Different Quantile Cutoffs

Quantile Cutoff:	**10%**	**20%**	**30% (baseline)**	**40%**	**50%**
Annualized Mean Return	10.7%	10.5%	**10.6%**	10.2%	9.5%
Annualized SD of Return	0.18	0.17	**0.17**	0.17	0.17
Sharpe Ratio	0.60	0.61	**0.61**	0.59	0.55
Observations	7,543	15,000	**22,471**	29,939	37,384
Significance*	0.99	0.98	**0.001**	0.99	0.99

* Paired one-sided t-test between the returns of high IP portfolios and the select STOXX Europe 600.

4.2 STOXX Europe 600: Long-short

Besides the long-only strategy described above, we also test a long-short strategy. The analysis structure will be similar to the preceding section: starting with an overview, we will investigate sector and market cap biases, and then sensitivity analysis with different quintile cutoffs.

a. Summary

Figure 2 shows the performance by longing the top 30% IP stocks and shorting the bottom 30%. The market-neutral strategy performs overall well despite the downward volatility during 2013-2015 and the upward volatility in early 2020.

Figure 2: Long Top 30% and Short the Bottom 30% In Select STOXX Europe 600

The annualized mean return from 2007-02-28t0 2020-05-31is 7.6%, its annualized standard deviation is 0.09. The market neutral strategy has a relatively stable cumulative return over the past 13 years.

Table 5: Long Top 30% and Short the Bottom 30%

	Annualized Mean Return	Annualized SD of return	Sharpe Ratio	Observations
Long-short with 30/30	7.6%	0.09	0.89	44,943

b. Bias

i. Sector

Similar to the discussion in the long-only, The baseline portfolio is decomposed into sectors shown in Table 6. The observations in the baseline portfolio are comparable to those in the data universe, the select STOXX, after breaking down into sectors. However, some sectors including materials, health care, industrial, and IT are heavily weighted in the long leg, while other sectors, especially financials, tend to be heavily weighted in the short leg. Due to the intrinsic sector bias, the long/short strategy tends to long or short some certain sectors, but does this intrinsic sector long/short strategy take account to all the alpha we saw in figure 2?

Table 6: Sector Bias with Long-short Strategy

Sector*:	**MA**	**HC**	**IN**	**IT**	**CS**	**CD**	**BL**
Annualized Mean Return	8.4%	1.7%	2.8%	8.6%	8.3%	3.7%	**7.6%**
Mean Net Weight	14%	18%	16%	8%	-2%	-1%	**0.0%**
Observations (% in baseline) (% in select STOXX)	4,303 (10%) (11%)	4, 890 (11%) (8%)	10, 470 (23%) (23%)	3,415 (8%) (6%)	2,715 (6%) (8%)	3,846 (11%) (11%)	**44,943**

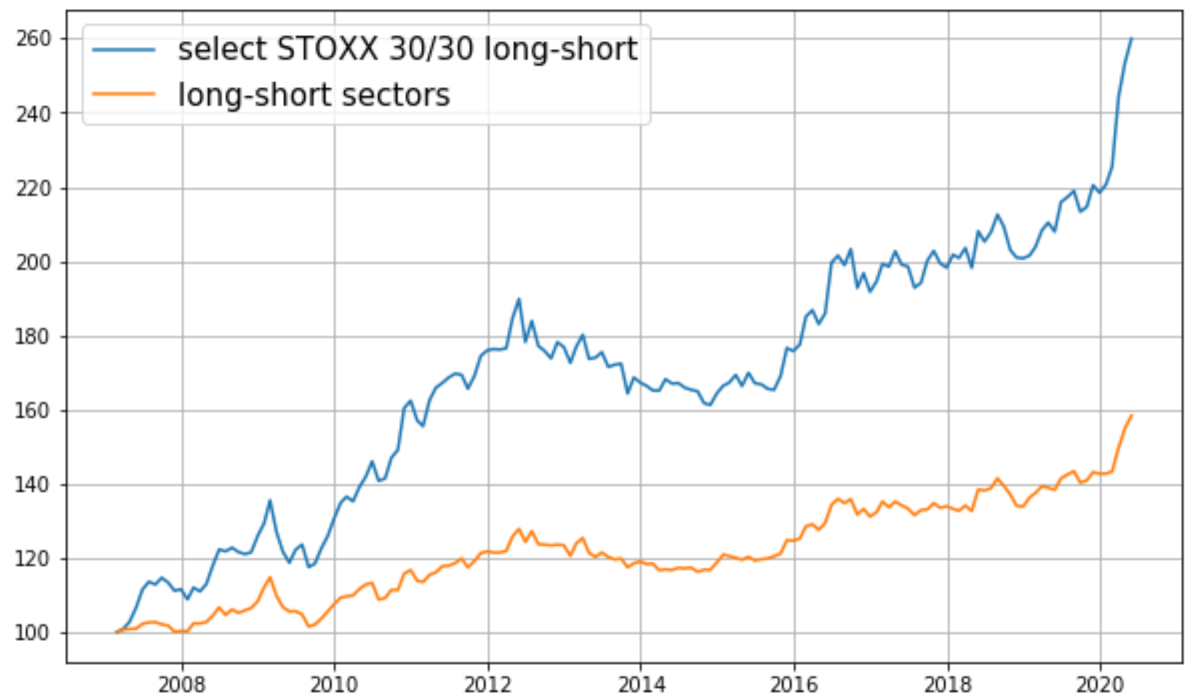
Sector:	**EN**	**COM**	**UT**	**FI**	**RE**	**BL**
Annualized Mean Return	-1.4%	-3.4%	- 39.8%	- 23.1%	- 19.8%	**7.6%**
Mean Net Weight	-2%	-6%	-8%	-35%	-0.7%	**0.0%**

Observations (% in baseline) (% in select STOXX)	1,438 (3%) (6%)	2,054 (5%) (8%)	2,182 (5%) (5%)	8,177 (18%) (13%)	408 (1%) (1%)	**44,943**

* Materials (M), Consumer discretionary (CD), Health care (H), Consumer staples (CS), Industrials (IN), Energy (EN), Information technology (IT), Communication Services (COM), Financials (FI), Real estate (RE), Utilities (UT), and Baseline (BL)

Keep this question in mind, we can actually decompose the alpha from sector long/short by synthesizing a sector-weighted portfolio. Based on the same data universe, we allocate the mean net weights to their respective sectors, this sector-weighted portfolio should be representative of the alpha contributed by sector allocation. Figure 3 shows the sector allocation does contribute to our long/short strategy - but only roughly half of it, the rest half return comes from PVE's promising stock picking ability.

Figure 3 30/30 Long-Short V.S. Pure Sector Long-Short



ii. Market Cap

Table 7 indicates the baseline portfolio has an overall long position in large-caps and short-position in mid-/small-caps. The total return basically comes from longing the large-caps and shorting the mid-/small-caps. What's more, the market cap bias is negligible as the cap size structure is very similar to the data universe.

Table 7: Market Cap Bias with Long-short strategy

Market Cap (EUR):	small-cap < 1B	mid-cap 1-10B	large-cap > 10B	All (baseline)
Annualized Mean Return	1.2%	7.2%	7.1%	**7.6%**
Mean Net Weight	-1.2%	-4.27%	5.5%	**0.0%**
Observations (% in baseline) (% in select STOXX)	2,502 (6%) (6%)	23,404 (52%) (52%)	19,037 (42%) (42%)	**44,943**

c. Quantile Cutoffs Analysis

The trading performance improves as the cutoff goes higher from 50% to 10%. Combining with the sensitivity discussion of long-only strategy, we can see that the short leg is contributing more when the cutoff goes from low to high.

Table 8: Long-short strategy with Different Quantile Cutoffs

Quantile Cutoff:	10/10	20/20	30/30 (baseline)	40/40	50/50
Annualized Mean Return	9.8%	7.8%	**7.6%**	6.32%	4.93%
Annualized SD of Return	0.12	0.1	**0.09**	0.07	0.06
Sharpe Ratio	0.80	0.81	**0.89**	0.87	0.82
Observations	15,086	30,000	**44,943**	59,879	74,768

5. Conclusion

We found the portfolio with high IP values outperforms the low IP group, it also significantly beats the benchmarks with P-value less than 0.01. Even though sector bias exists, it does not essentially come from the historical sector performance, the alpha source is generated from IP alpha. What's more, the market cap bias is either negligible or tends to be overweight on large-caps.