WORKING paper

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Macroeconomic Forecasting Using Filtered Signals from a Stock Market Cross Section

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Abstract

Stock prices declined abruptly in the wake of the Covid-19, reflecting both the deterioration of investors' expectations of economic activity as well as the surge in risk aversion. In the following months, however, economic activity remained sluggish while equity markets bounced back. This disconnect between equity values and macro-variables can be partially explained by other factors, namely the decline in risk-free interest rates, and -for the US- the strong profitability of the IT sector. As a result, an econometrician forecasting economic activity with aggregate stock market variables during the Covid-crisis is likely to get poor results. Our main contribution is thus to rely on sectorally disaggregated equity variables within a factor model in order to predict US economic activity. We find, first, that the factor model better predicts future economic activity compared to aggregate equity variables, or to conventional benchmarks used in the literature, both in-sample and out-of-sample. Second, we show that the strong performance of the factor model comes from the fact that it filters out the "expected returns" component of the sectoral equity variables as well as the foreign component of aggregate future cash flows. The constructed factor overweights upstream and "value" sectors that are found to be closely linked to the future state of the business cycle.[4]

Keywords: Factor Model; Equity Markets; Macroeconomic Forecasting.

JEL classification: E17,G14,G17

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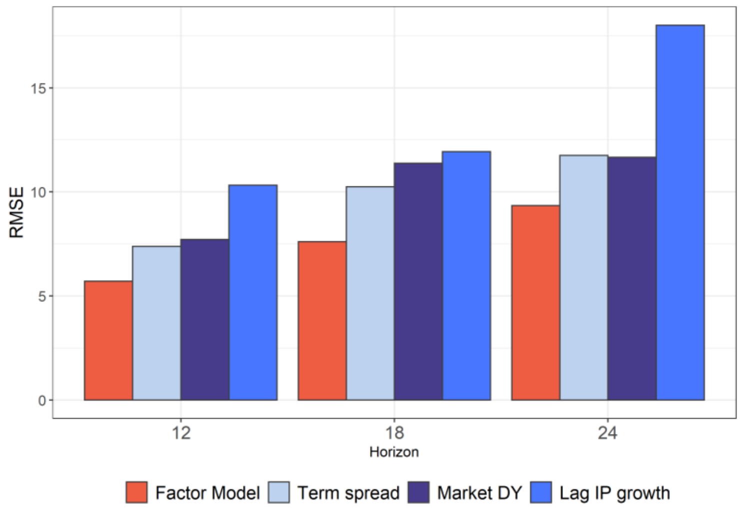
NON-TECHNICAL SUMMARY

After the Covid shock in March 2020, aggregate stock prices declined abruptly, reflecting both the deterioration of expectations of future economic activity as well as the surge in risk aversion. In the following months, however, and to the surprise of many, whereas economic activity remained sluggish, equity markets bounced back sharply. As a result, an econometrician forecasting economic activity with *aggregate* stock variables during the Covid-crisis would likely have obtained poor results.

The idea of this paper is to rely, within a factor model, on *sectoral* stock variables to predict future Industrial Production (IP) growth in the US. Surprisingly enough, whereas disaggregated equity data is easily available without lags, to our knowledge the literature on factor models rarely relies on sectoral stock data, and never estimated specifically a factor out of sectoral equity variables only. This paper constitutes thus the first application of a factor model to extract the predictive content from these sectoral equity variables.

On the result side, we find first that our factor based on sectoral dividend yields (DYs) better predicts IP growth, as compared to the same variable measured as an aggregate and to other conventional benchmark models (both in-sample and out-of-sample, and at various horizons, see Graph below).
Second, we show that our model improves forecasting accuracy because it filters out the noisy components of equity variables, namely the expected returns/discount rate component, as well as the foreign component of aggregate future cash flows.
Third, we are able to identify the sectors that provide additional forecasting power. Specifically, we find that our factor model overweights upstream sectors (primary industry and other industrial inputs) and "value" sectors, as the latter are found to be closely linked to the US business cycle.
To conclude, we find that the factor model is better able to forecast IP, and particularly so during periods of negative growth. As a consequence, our model has greater precision exactly at times of economic stress. For practioners (policymakers or central bankers for example) this attribute is of particular importance given that these periods are often characterized by elevated macro-uncertainty and the need for reliable business cycle predictions.

Out-of-Sample RMSE from the different estimated models



Note: On the graph are represented the Out-of-Sample RMSE of different models (the factor model or univariate regressions relying either on the aggregate DY, on the lagged IP growth or on the term spread). The predicted variable is the IP growth over 12, 18 and 24 months.

Prévision macroéconomique à l'aide du signal tiré des données sectorielles des marchés actions

RÉSUMÉ

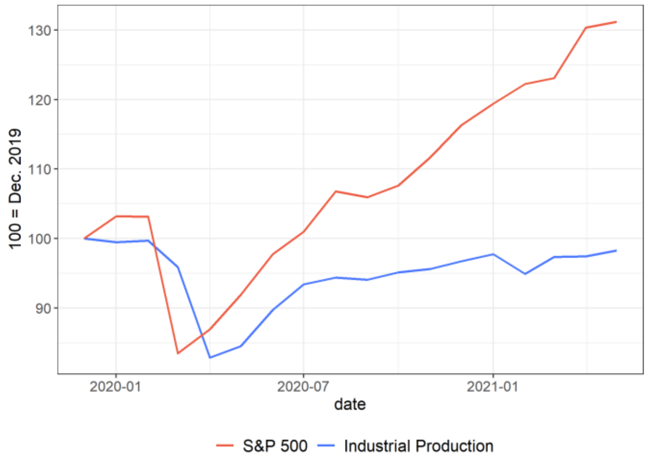
À la suite du choc du Covid-19, les marchés actions ont fortement décliné. Toutefois, sur les mois qui suivirent, alors que l'activité économique restait morose, les indices boursiers augmentèrent significativement. Cette apparente déconnexion entre les marchés actions et les variables macros peut être en partie expliquée par d'autres facteurs, notamment par la baisse des taux sans risque sur la période ainsi que, pour les États-Unis, par la forte profitabilité du secteur du numérique. Par conséquent, un économètre essayant de prédire l'activité économique à l'aide des données actions *agrégées* durant la crise du Covid aurait certainement eu de mauvais résultats. La principale contribution de ce papier est ainsi d'utiliser les données actions *sectorielles*, dans le cadre d'un modèle à facteurs, pour prédire l'activité économique américaine. Nous trouvons premièrement que notre modèle à facteurs fournit des prévisions plus précises notamment par rapport aux variables agrégées du marché actions. Deuxièmement, nous montrons que la surperformance de notre modèle provient du fait qu'il filtre les composantes du marché actions ne reflétant pas les anticipations d'activité économique (les variations du taux d'actualisation et la composante des futurs dividendes liée aux activités à l'étranger des firmes US). Enfin nous relions également la capacité prédictive de notre modèle au fait qu'il surpondère les secteurs situés en amont des processus de production industriels.

Mots-clés : modèles à facteurs; marchés actions; prévision macroéconomique

1. Introduction

The use of financial variables to predict economic growth has a long history, with one early paper (Fischer and Merton, 1984) linking stock returns and subsequent industrial production growth. And yet, despite the fact that financial variables impound expectations of future economic activity, and hence should well-predict the latter, the case for stock market variables has not been made convincingly. For instance, in a representative finding, Estrella and Mishkin (1998) conclude that bond market variables outpredict stock market variables. More concretely, the recent divergence between developments in equity markets and subsequent economic activity has only highlighted the apparent disconnect between finance and the real economy. After the Covid shock in March 2020, stock prices declined abruptly, reflecting both the deterioration of investors' expectations of future economic activity as well as the surge in aggregate risk aversion. In the following months, however, and to the surprise of many, whereas economic activity remained relatively sluggish, equity markets bounced back sharply, as illustrated in Figure 1.

Figure 1: S&P 500 and US Industrial Production (100 = Dec.2019)



Note: The graph represents the evolution of the US Industrial Production and of the S&P 500 Index. Both indices are set to 100 in December 2019. Sources: Federal Reserve Economic Data, Refinitiv Datastream.

A simple, but incomplete, explanation is that not only do stock prices reflect expected future cash flows and investors' risk aversion, but also the level of risk free interest rates. Focusing on the American example, US 10 year sovereign rates declined from March to August 2020 and can therefore explain part of the equity rebound (Chatelais and Stalla-Bourdillon, 2020). This seeming disconnect between stock market developments and the real economy can be more fully reconciled with the data by recognizing that reliance on a single aggregate stock price index discards a lot of information that might be of particular importance, especially during business cycle turning points. For example the S&P 500 was driven up in 2020 by IT sector companies whose valuations either largely depend on foreign activity or are orthogonal to US economic performance as their profitability derived tremendously from Covid19 lockdown policies. As a result, an econometrician forecasting economic activity with aggregate stock variables during the Covid-crisis would likely to obtain poor results.

In this paper, we provide an explanation for why aggregate, or economy-wide, stock market variables fail to provide accurate forecasts of economic activity. We do this by building a factor model constructed using sectorally disaggregated equity variables. Hence, this study constitutes one of the rare instances where stock market variables specifically are used to perform macroeconomic forecasting. Furthermore, this study adds to a surprisingly small forecasting literature relying on *sectorally disaggregated* equity variables, and constitutes the first application of factor models to extract the predictive content from these sectoral stock variables. Even papers employing factor models based on large sets of variable seldom go beyond using aggregate stock indices (Barhoumi, Darné and Ferrara, 2010, Jardet and Meunier, 2022).

We obtain three main results, relating to forecasting performance.

First, we find that a factor based on sectoral dividend yields (DYs) better predicts industrial production (IP) growth, as compared to the same variable measured as an aggregate. That factor model also typically outperforms conventional benchmark models, such as the term spread or the lagged IP growth, particularly during times of negative IP growth. This is true at the 12, 18 and 24 month horizons, and both in- and out-of-sample. We also find that our factor model helps to improve the forecasting accuracy of a widely used factor model à la Stock and Watson (2002) that relies on a vast number of macro-financial variables (but not on sectoral equity indices). Interestingly, our finding generalizes to a number of other countries.[1]

Second, relying upon the present value formula of Campbell and Shiller (1988), we conclude that our model improves forecasting accuracy because it filters out the expected returns/discount rate component of the sectoral equity variables, as well as the foreign component of aggregate future cash flows. We attribute the elevated outperformance of our factor model, especially during periods of negative IP growth such as during the Covid pandemic or during the Global Financial Crisis, to this filtering out of extraneous information. As expected returns are more volatile in recessionary states (Henkel et al., 2011) they tend to particularly affect the forecasting accuracy of the aggregate DY during these periods, but not of our factor model.

Third, we are able to identify the specific sectors that provide additional forecasting power. Specifically, we find that our factor model overweights upstream sectors (primary industry and other industrial inputs) and "value" sectors, as the latter are found to be closely linked to the US business cycle (Zhang, 2005, Koijen, Lustig and van Nieuwerburgh, 2017, Xu, 2018). Our model's superior forecasting performance during periods of negative IP growth makes sense given the overweighting of cyclically sensitive sectors.
In the following section, we present the basic theory placed in the context of the literature. In Section 3 we present the empirical model and detail the data used in the analysis. Section 4 provides a set of in-sample results, and Section 5 a corresponding set of out-of-sample results. We draw out the economic implications of those results in Section 6. Concluding Remarks are contained in Section 7.

2. Background

2.1 Theoretical Framework

When using aggregate financial measures to predict economic activity, one wants the factors influencing the financial variables to correspond to the appropriate macroeconomic variable. Since our objective is to forecast US economic activity, we want our financial predictor to reflect solely US activity. In order to extract the US component, we rely upon the present value formula of Campbell and Shiller (1988), a decomposition that has been widely used to model equity returns (see Campbell and Ammer, 1993, Vuolteenaho, 2002, and van Binsbergen and Koijen, 2010).

More precisely, DYs (x_t) can be decomposed into two factors: expected returns (or discount rates) and expected cash flow growth likewise:

$$x_t = \frac{\kappa}{1-\rho} + \sum\nolimits_{j=1} \rho^{j-1} E_t[r_{t+j} - \Delta cf_{t+j}]$$

[1] The outperformance also extends to specifications including some measure of volatility, such as the VIX. This point, as well as the results regarding other countries industrial production growth, are discussed in the Section 5.1.

Where $E_t[r_{t+j}]$ represents expected returns and $E_t[\Delta cf_{t+j}]$ expected cash flows (κ and ρ are constant parameters). One could also decompose the cash flow component into two sub-components: one depending on the domestic activity of the firm, $E_t[\Delta cf_{D,t+j}]$, and the other one stemming from its foreign activity, $E_t[\Delta cf_{F,t+j}]$, such that we would get:

$$x_t = \frac{\kappa}{1-\rho} + \sum\nolimits_{j=1} \rho^{j-1} E_t[r_{t+j} - \Delta cf_{D,t+j} - \Delta cf_{F,t+j}]$$

Note eventually that a similar decomposition can be applied to other equity variables, such as price-earnings or book-to-market ratios.

In order to forecast future aggregate returns, Kelly and Pruitt (2013) underline that the usual predictive regressions of aggregate future returns and aggregate dividend growth on aggregate DY:

$$r_{t+h} = \alpha_1 + \beta_1 x_t + u_{1,t+h}$$

$$\Delta cf_{t+h} = \alpha_2 + \beta_2 x_t + u_{2,t+h}$$

are misspecified, since the aggregate DY both reflects expected returns and expected cash flows, while they would like this variable only to reflect the former (when predicting aggregate returns), or the latter (when predicting aggregate dividend growth).

Relying on disaggregated book-to-market ratios, which can also be decomposed with the Campbell and Shiller (1988) formula, Kelly and Pruitt (2013) estimate a factor model via Partial Least Squares on that appears to predict accurately future aggregate returns and future aggregate dividends. They explain the improved accuracy by the fact that the factor model, by overweighting or underweighting certain sectoral book-to-markets, filters out the expected cash flow component while predicting future aggregate returns (and vice versa when predicting future aggregate dividends).

In an approach similar to theirs, we implement the same filtering to extract a factor to predict future economic activity. In our case we want the factor model to not only filter out the expected returns component, but also the foreign cash flow component. Implicitly, we assume that the domestic cash flow component represents a good proxy for domestic US economic activity. We also assume that this filtering is possible because sectoral DYs are informative about future aggregate cash flows. We return to this point more formally in Section 9.1 of the Appendix.

2.2 Selected Literature Review

There are three strands of the literature relevant to our contribution. The first is the literature using stock prices to predict economic activity. The second is the use of factor modeling for forecasting purposes. The third focuses on how expectations regarding future economic activity affect the cross section of returns.

Turning to the first strand, the theoretical arguments underlining the predictive power of stock prices are twofold (Croux and Reusens, 2013). On one hand equity prices are inherently forward looking and should therefore reflect investors' expectations of future economic activity. On the other hand, stock prices can have a causal effect on the business cycle: if stock prices go up, households should consume more through the induced wealth effect. Hence, stock prices should lead aggregate activity. Consequently, various papers try to predict future GDP or industrial production with equity variables, typically with aggregate stock indices (Binswanger, 2000, Henry, Olekalns and Thong, 2004 Croux and Reusens, 2013, McMillan, 2021, Chen and Rancière, 2019, Lan, 2020) or with variables related to aggregate indices, such as market skewness (Chen et al., 2019).

Some papers, however, rely on *disaggregated* stock price data and can be further divided into two subcategories. In the first subcategory are papers that first build an aggregate variable from sectoral equity data and then forecast future activity with the former. Loungani, Rush and Tave (1990) for example use industry-level equity prices to build a metric of price dispersion. They reason that if stock prices are increasing in some industries but declining in others, in subsequent years capital and labor will have to be reallocated from the contracting industries to the expanding ones, which will be costly in the aggregate. Liew and Vassalou (2000) rely on the Fama-French factors, built from disaggregated portfolio returns, to forecast future GDP. Their rationale is that, before a recession, investors should be able to anticipate that small stocks and value stocks will perform badly. Indeed, small-sized firms and value companies, i.e. firms with low price-earnings ratios and typically elevated fixed capital as in the automobile industry, are usually deemed as less resilient to strong negative shocks (Zhang, 2005, Xu, 2018). As a result, small minus big (SMB) returns and high minus low (HML) book-to-market returns should decrease ahead of recessions. In the second subcategory are other papers that directly use the sectoral equity variables in their estimation, most of the time by evaluating the predictive power of specific sector variables in isolation from the other (Browne and Doran, 2005, Andersson and d'Agostino 2008, Zalgiryte, Guzavicius and Tamulis, 2014).

Our main contribution is that we depart from the approach adopted in these previous papers first by estimating a factor model based on sectoral equity variables. We therefore make use of the *entire cross section* of stock market variables at the same time (in contrast to Browne and Doran, 2005, Andersson and d'Agostino 2008, Zalgiryte, Guzavicius and Tamulis, 2014). Moreover, we do not constrain the predictive content of disaggregated stock variables into a specific aggregate predictor, like the dispersion of stock prices or the Fama-French factors. Second, again in contrast to all the papers cited above, we also investigate the over- and under-weights of the different sectors in our factor model.

In the end, our approach comes closest to two papers that also rely on the Kelly and Pruitt (2013, 2015) factor model to predict macroeconomic activity on the basis of equity variables. However, unlike our approach, they either use aggregate – and not sectoral -- indices to build their factor, i.e., the number of IPOs or the share turnover in the US (Huang, Jiang, Tu and Zhou, 2015), or they only perform their analysis in-sample and do not analyze what is filtered out in their factor modelling (Jagannathan and Marakani, 2015).

Second, we also contribute to the literature on factor modelling that does not specifically focus on the predictive content of equity variables. Surprisingly enough, whereas disaggregated equity data is easily available and is accessible without lags, to our knowledge the literature on factor models for forecasting exercises rarely relies on sectoral stock data, even when using large datasets (Bessec and Doz, 2012, Fan, Xue and Yao, 2017, Hepenstrick and Marcellino, 2019, Ferrara and Marsilli, 2019, Jardet and Meunier, 2022) or when using other types of sectoral variables, like surveys (Barhoumi, Darné and Ferrara, 2010).

Finally, we also contribute to the financial literature that takes perspective inverse of the standard, by evaluating how future economic activity affect aggregate (Cenedese and Mallucci, 2016) as well as cross-sectional stock returns (Koijen, Lustig and van Nieuwerburgh, 2017, Zhu, Ghao and Shermann, 2020). By analyzing how the factor model over/underweights certain equity sectors we shed a new light on the pro- and counter-cyclicality of specific portfolios.

3 Model Specification and Data

3.1 A Factor Model

We follow Kelly and Pruitt (2013, 2015), who utilize the Partial Least Square (PLS) methodology estimated using disaggregated equity variables. The approach resembles Principal Components Analysis (PCA), but instead of reducing the dimensionality according to the covariance of the sectoral variables between themselves, we implement the reduction according to the covariance between the predicted variable and the sectoral variables.

Starting with y_{t+h} the predicted variable (in our case, the growth rate of Industrial Production) and x_{it} the different sectoral equity variables (here the sectoral DYs), the PLS is estimated in three steps.

First, for each sector i, a univariate time series regression is estimated:

$$x_{it} = \phi_{i0} + \phi_i y_{t+h} + e_{it}$$

Second, for each time period t, the sectoral DYs x_{it} are regressed on the coefficients $\widehat{\phi_\iota}$ estimated above. Note that this regression is a cross-sectional one, and that the estimated coefficient will be the value of the factor F_t at time t:

$$x_{it} = c_t + F_t \widehat{\phi_\iota} + \omega_{it}$$

Finally, we use the estimated factor in a (time series) predictive regression:

$$y_{t+h} = \beta_0 + \beta_1 \hat{F}_t + u_{t+h}$$

The estimated factor $\hat{F}_t$ can be seen as a weighted sum of the different x_{it} since:

$$\widehat{\phi_\iota} = \frac{\sum_t (x_{it} - \bar{x_\iota})(y_{t+h} - \bar{y})}{\sum_t (y_{t+h} - \bar{y})^2} \text{ with: } \bar{x_\iota} = \frac{1}{T}\sum_t x_{it} \text{ and: } \bar{y} = \frac{1}{T}\sum_T y_{t+h}$$

And since:

$$F_t = \frac{\sum_i (x_{it} - \bar{x_\iota})(\widehat{\phi_\iota} - \bar{\phi})}{\sum_i \left(\widehat{\phi_\iota} - \bar{\phi}\right)^2} \text{ with: } \bar{\phi} = \frac{1}{I}\sum_i \widehat{\phi_\iota} \text{ and:} \bar{x_t} = \frac{1}{I}\sum_i x_{it}$$

We can therefore write:

$$\widehat{F_t} = \frac{1}{C}\sum_i x_{it}(\widehat{\phi_\iota} - \bar{\phi}) \text{ with: } C = \sum_i \left(\widehat{\phi_\iota} - \bar{\phi}\right)^2$$

In other words, the more x_{it} is correlated with y_{t+h} the more it will influence $\hat{F}_t$ through the coefficients $\left(\widehat{\phi_\iota} - \bar{\phi}\right)$.

3.2 Data

Throughout the paper we focus on the United States. In our main specification, we predict future Industrial Production growth. Depending on the forecast horizon h, and with IP_t the Industrial Production index, we forecast at time t the variable:

$$y_{t+h} = \frac{IP_{t+h}}{IP_t} - 1$$

The DYs are drawn from Refinitiv Datastream indices either collected to reflect the overall US equity market or sectoral portfolios. The sectoral indices are based on the Industry Classification Benchmark (IBC), and are available at different granularity: either 11, 20 or 44 sectors. We rely on the most detailed breakdown available (44 sectors), although we retrieve from it 4 sectors for which the DY series were incomplete: Alternative Energy, Closed end Investments, Precious Metals and Mining and Mortgage Real Estate Investment Trusts. Thus in our main exercise we forecast IP growth with a factor model based on 40 different DY series. In the paper we also consider the aggregate DY, which corresponds to the average DY of the US stock market, also collected by Refinitiv Datastream.

The other macroeconomic and financial data sources are from sources detailed in Table 8 of the Appendix. The data is at a monthly frequency, spanning the period from 02-1973 (the earliest date available for the sectoral

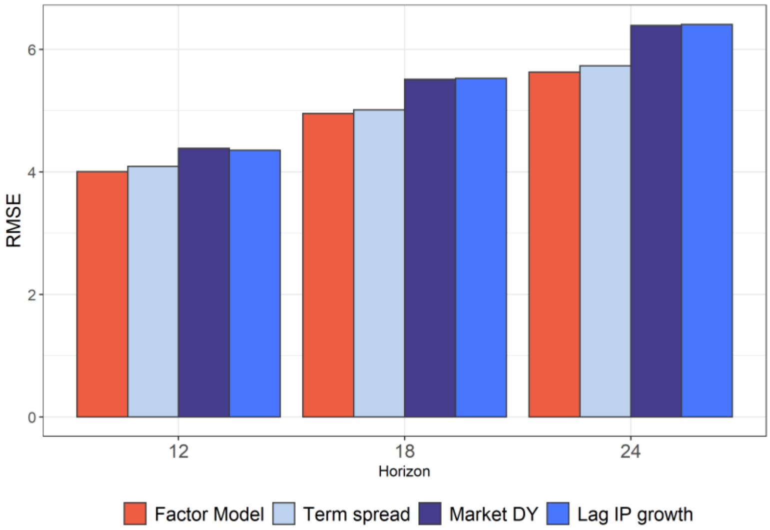
DYs drawn from Refinitiv Datastream) to 05-2021. We define the term spread as the spread between the Treasury 10 year and 3 month yields, in line with Chinn and Kucko (2015).

4 In-Sample Results

In order to determine whether our disaggregated equity variable based factor model exhibits greater predictive power than models based on aggregate DY, or conventional benchmark models, we conduct both in-sample and out-of-sample analyses. In this section, we present the former set of results, reserving the latter for Section 5.

To summarize the prediction results, in Figure 2 we present the in-sample RMSE of different predictive models at various horizons. In light blue, purple and dark blue bars are represented, respectively, simple forecasting models based either on the term spread, on the aggregate DY or on the lagged IP growth. The in-sample RMSE based on the factor model is shown as the red bar.

Figure 2: In-Sample RMSE from the different estimated models



Note: On the graph are represented the In-Sample RMSE of different models (the factor model or univariate regressions relying on the aggregate DY, on the lagged IP growth or on the term spread). The predicted variable is the IP growth over 12, 18 and 24 months.

Several findings are readily apparent. First, irrespective of the horizon, the factor model constantly beats the conventional benchmarks, that is the lagged IP growth or the term spread, although the term spread appears as the second best performing model.

Second, the factor model outperforms the simple predictive regression based on aggregate equity data (here the aggregate DY), thus highlighting the additional accuracy that can be gained from working with sectoral stock market variables. For this last result, it should however be borne in mind that, in an in-sample setting, our factor model should in any case outperform the aggregate DY given that it overweights the sectoral DYs which are the most correlated with future IP growth.

Focusing on the 12-month horizon, we show on Figure 7 of the Appendix that the same in-sample results hold when we look at alternate proxies of economic activity, although the outperformance with respect to the term spread appears more mixed. We considered manufacturing sales, the number of house permits delivered, the OECD indicator of monthly US GDP, the US unemployment rate or total nonfarm payroll employment.

We perform a second simple in-sample evaluation by determining whether or not the estimated factor brings additional information as compared to our main benchmark (here the aggregate DY, x_t). To do so, we run the following predictive regression:

$$y_{t+h} = \beta_0 + \beta_1 x_t + \beta_2 \widehat{F}_t + u_{t+h}$$

And evaluate the significance of the coefficient β_2. Table 1 below reports the results of these in-sample regressions at horizon 12, 18 and 24 months. To account for the serial correlation of the error terms, we conduct our statistical inference using Newey-West standard errors. Notice in Table 1 that the coefficient associated with the factors built on sectoral equity variables is significant for all different horizons. This result thus suggests that the factor model has forecasting value even with the inclusion of the aggregate DY in the regression.

Table 1: Predictive coefficients of the estimated factor
(In-sample estimates)

	Dependent variable:		
		IP Growth	
	12 months	*18 months*	*24 months*
Market DY	−0.014*	−0.015	−0.014
	(0.008)	(0.012)	(0.014)
Factor	0.282**	0.297***	0.313***
	(0.125)	(0.112)	(0.116)
Constant	0.038*	0.039	0.035
	(0.022)	(0.035)	(0.046)
Observations	532	526	520
R2	0.265	0.270	0.285
Adjusted R2	0.262	0.267	0.282
F Statistic	95.295***	96.723***	103.059***
	(df = 2; 529)	(df = 2; 523)	(df = 2; 517)

*Note: The reported regressions are made using Newey-West heteroskedasticity and serial correlation robust standard errors. * p<0.1 ; **p<0.05 ; ***p<0.01*

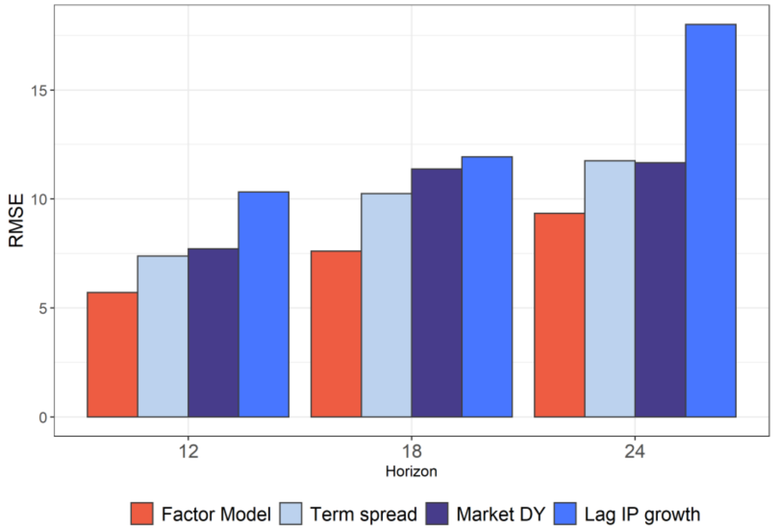
5 Out-of-Sample Results

5.1 Out-of-Sample Performance

We conduct an out-of-sample forecasting exercise in order to guard against overfitting. Following the same procedure outlined in Section 4, we set the rolling window used for estimation to 36 months (3 years). This means that for a 12-month horizon, the first observation to be predicted is January 1977. Our results are robust to consideration of shorter or longer rolling windows. Note that for the out-of-sample exercise, we closely follow the procedure described in Kelly and Pruitt (2013), so that, when predicting IP growth at time *t+h* based with variables at time *t*, all the regressions outlined in Section 3 are based on training samples that exclude observations posterior to time *t*.

Figure 3 indicates, in a format similar to that in Figure 2, the out-of-sample RMSE estimated for the different models. In line with the in-sample analysis, relying on disaggregated -- rather than on aggregate -- equity variables dramatically improves the forecasting accuracy of our model. Again, this improvement is noticeable through all the different considered horizons. Regarding the relative performance of the other benchmarks, here also the factor model appears to outperform the term spread or the lagged IP growth. Finally, we run the same robustness check as in the in-sample exercise and assess the predictive accuracy of the different models for the other proxies of economic activity. As shown in Figure 8 in the Appendix, the factor model strongly improves our forecasting accuracy for virtually all the different predicted variables, sometimes decreasing the out-of-Sample RMSE by close to 20%, relative to the best performing benchmark.

Figure 3: Out-of-Sample RMSE from the different estimated models



Note: On the graph are represented the Out-of-Sample RMSE of different models (the factor model or univariate regressions relying either on the aggregate DY, on the lagged IP growth or on the term spread). The predicted variable is the IP growth over 12, 18 and 24 months.

As common in the forecasting literature (Hepenstrick and Marcellino, 2019, Jardet and Meunier, 2022), we further assess the outperformance of the factor model with respect to the different benchmarks by conducting Diebold-Mariano tests for statistical significance (West, 1996, Diebold and Mariano, 2002). Table 2 reports the difference in RMSE between the factor model and the different benchmarks, along with the Diebold-Mariano p-values under the null hypothesis that the factor model performs worse than the corresponding benchmarks.

Overall, in line with Figure 3 and at the notable exception of the term spread at the 12-month horizon, we find that the factor model improves significantly the prediction of future IP growth compared to the three different benchmarks, and at the three different horizons[2].

[2] The performances of our factor model appear more mixed at shorter horizons. Compared to a univariate model based on the aggregate DY, our factor model does not improve the forecasting accuracy at the 1-month horizon, but exhibits a lower RMSE at the 3-and 6-month horizons, although the difference in RMSE is not significant in lights of Diebold-Mariano tests.

Table 2 : Difference in RMSE with the main benchmark models
(Factor model – Corresponding benchmark, Out-of-sample estimates)

Benchmark:	*Horizon:*		
	12 months	*18 months*	*24 months*
Market DY	-2.01*	-3.76*	-2.33***
Term spread	-1.68	-2.63*	-2.41***
Lagged IP growth	-4.62**	-4.32***	-8.67***

*Note: The table reports the difference in RMSE of the factor model compared to the different benchmarks (a negative value means that the factor model outperforms the corresponding benchmark in terms of RMSE). Stars represent the Diebold-Mariano test p-values under the null hypothesis that the factor model performs worse than the benchmark models indicated in the first column. * p<0.1 ; **p<0.05 ; ***p<0.01*

We eventually run two out-of-sample exercises to underline the performance of our factor model. First, we evaluate the accuracy of our model compared to forecasting regressions using different metrics of market volatility. Either we rely only on the volatility variables alone in univariate regressions, or we augment the models with the term spread given that recent papers underlined that market volatility may prove useful to extract the forecasting signal out of the term spread (Kumar et al., 2022, Natoli and Venditti, 2022). Table 6 in the Appendix reports the differences in RMSE between these benchmarks and our factor model. As could be seen on the Table, it appears that our model significantly outperforms the aforementioned benchmarks, at various horizons and for different proxies of market volatility.

Second, we vet whether our results remain robust for other advanced economies. To do so, we collect data for 5 additional countries: Canada, France, Germany, Switzerland and the United Kingdom. We report on Table 7 of the Appendix the differences in RMSE, for each country, between the same benchmark models[3] as in Figure 3 and our factor model for a 12-month horizon forecasting exercise. As can be seen on the Table, on the 15 different specifications considered here, our factor model appears to outperform the benchmarks in 12 cases. For France and the United Kingdom our factor model exhibits a lower RMSE compared to a univariate regression based on the lagged IP growth, but the difference does not appear significant. Only with respect to French term spread does our factor model display a higher RMSE when it comes to forecasting IP growth.

5.2 Comparison with traditional factor models

In addition, we investigate whether our factor, based on sectoral equity variables, can be used to improve more conventional factor models that rely on macroeconomic variables and on aggregated financial indicators. Indeed, whereas sectoral equity variables are easily available and published without lags, they seem to be rarely used in the forecasting literature relying on large datasets (Barhoumi, Darné and Ferrara, 2010, Hepenstrick and Marcellino, 2019, Jardet and Meunier, 2022).

To do so, we build a large dataset of 147 variables that includes aggregate macroeconomic indicators (CPI, unemployment rates), disaggregated macroeconomic variables (sectoral retail sales, sectoral industrial production indices) and aggregate financial indicators (exchange rates, interest rates and equity variables). A detailed list of the variables used is available in Table 8 of the Appendix. In the spirit of Stock and Watson

[3] For each country, the Market DY, the IP growth and the term spread are all collected from Refinitiv Datastream.

(2002), we then extract factors $\boldsymbol{H}_t$ from this dataset with a simple Principal Component Analysis.[4] The question is then whether our factor, based on disaggregated equity variables, F_t, helps to improve the (out-of-sample) forecasts made with PCA-factors $\boldsymbol{H}_t$, without the use of these precise variables.

To that aim, based on the same rolling window length, we compare the forecasts made by estimating a model relying on the PCA-factors:

$$y_{t+h} = \beta_0 + \boldsymbol{\beta}_1' \boldsymbol{H}_t + u_{t+h}$$

And a model relying on the PCA-factors along with the lag of the predicted variable:

$$y_{t+h} = \beta_0 + \boldsymbol{\beta}_1' \boldsymbol{H}_t + \beta_2 y_t + u_{t+h}$$

With the same models augmented with our factor, that is:

$$y_{t+h} = \beta_0 + \boldsymbol{\beta}_1' \boldsymbol{H}_t + \beta_2 F_t + u_{t+h}$$

And:

$$y_{t+h} = \beta_0 + \boldsymbol{\beta}_1' \boldsymbol{H}_t + \beta_2 y_t + \beta_3 F_t + u_{t+h}$$

We are agnostic regarding the number of relevant PCA-factors and therefore include in our regressions 1 to 3 PCA-factors. Table 3 below summarizes the differences in RMSE of the aforementioned models, augmented or not with our factor stemming from the sectoral equity variables. As the models that we compare are nested, the reported p-values in Table 3 stem from Clark and West (2007) tests.

In Table 3, notice that augmenting the PCA-factors with the factor built with the sectoral DYs improves the RMSE in virtually all cases, with RMSE gains being significant in two thirds of the considered cases. This highlights the extra information that can be gained with disaggregated equity variables.

5.3 Performance by Sample Period

In the Introduction, we outlined that the gains of relying on sectoral rather than on aggregate equity variables may especially be strong in times of negative economic growth, such as during the pandemic. This may be the case if, for example, in these periods aggregate DY is driven mostly by sectors which are only loosely linked to the future economic activity, or if variations in aggregate DY reflect more changes in investors' discount rates/expected returns rather than changes in earnings expectations.

Although we return to more formally discuss these economic mechanisms in Section 6, in this section, we investigate whether the forecasting performance of our factor model differs between periods of contraction and of expansion. In Table 4, we define periods of contraction as months during which the annual IP growth is negative (and the reverse for periods of expansion). In line with Moench and Stein (2021), the Table reports the difference in RMSE between our factor model based on sectoral equity variables and the same univariate model benchmarks outlined in Section 5.1 (along with the p-values of Diebold Mariano tests). Note that we segment here our estimation according to the dates in which the forecasts are made. In other words, if we consider here a forecast horizon of 12 months, the ''Negative IP growth'' period refers to predictions made when the annual IP growth was negative (and not predictions made 12 months before the contraction in economic activity).

[4] We applied Dickey-Fuller tests to all the variables and transform them into growth rates in cases where we could not reject the null hypothesis of a unit root. We make several exceptions to that rule though, in the sense that we also include the benchmark variables of Section 5.1 in levels and we also incorporate several financial variables in log returns.

Table 3 : Difference in RMSE with alternative factor models
(Factor model – Corresponding PCA-factor benchmark, Out-of-sample estimates)

Benchmark:	*Horizon:*		
	12 months	*18 months*	*24 months*
1 PCA-Factor	-5.72*	-13.31*	-8.16*
1 PCA-Factor with lagged IP growth	-3.43**	-8.49	-7.79**
2 PCA-Factors	-0.17**	-0.16**	-0.58*
2 PCA-Factors with lagged IP growth	-0.85	-1.29	-7.54
3 PCA-Factors	-0.18***	-0.36*	-0.76*
3 PCA-Factors with lagged IP growth	-5.62**	-0.69	-6.55

*Note: The table reports the difference in RMSE of the models indicated in the first columns (augmented with the factor F_t stemming from the sectoral equity variables) with respect to the same models without this specific factor. A negative value means that augmenting the model with the factor F_t improves the RMSE. Stars represent the Clark and West (2007) test p-values under the null hypothesis of equal MSPE. * p<0.1 ; **p<0.05; ***p<0.01*

Note that in Table 4, although our factor model outperforms other benchmarks both in periods of negative and positive IP growth, the gain in forecast accuracy of our factor model appears to be strongly concentrated in negative IP growth period. The difference between the two periods can be substantial: looking at the 12-month horizon for example, relying on our factor based on sectoral DYs rather than on the aggregate DY can yield a RMSE-gain close to 4 times higher in negative IP growth period than in positive growth period.

One potential interpretation is that expected returns/discount rates are more volatile during recessions (Henkel et al., 2011), and can therefore blur the forecasting ability of the aggregate DY in those times. In contrast, as outlined in next section, given that our factor model filters out the expected returns component of sectoral DYs, it can yield strong forecasting accuracy gains in periods of contracting economic activity. As an example, in 2009, close to the end of the Great Recession, the aggregate DY was still very high, notably because investors' risk aversion, and thus investors' discount rates, were very high as well. As a result, the 12-month ahead IP growth forecast from the aggregate DY was still very pessimistic (-29.1% in May 2009 for the next year IP growth). In contrast, the forecast from the factor model was much closer to the realized IP growth at the same time (+6.2% against a realized value, in May 2010, of +7.9%), likely because the forecasting ability of our factor model was not affected by this elevated discount rate component.

Table 4 : Difference in RMSE by Period
(Factor model – Corresponding benchmark, Out-of-sample estimates)

Benchmark:	*Period:*	*Horizon:*		
		12 months	*18 months*	*24 months*
Market DY	Negative IP growth	-3.8*	-7.06**	-6.82***
Market DY	Positive IP growth	-1.05**	-0.82***	-0.33
Term spread	Negative IP growth	-3.47*	-8.05**	-6.62***
Term spread	Positive IP growth	-0.67**	0.17	-0.58
Lagged IP growth	Negative IP growth	-8.71**	-9.59***	-21.71***
Lagged IP growth	Positive IP growth	-2.31**	-3.21***	-1.5***

*Note: The table reports the difference in RMSE of the factor model compared to the different benchmarks (a negative value means that the factor model outperforms the corresponding benchmark in terms of RMSE). Stars represent the Diebold-Mariano test p-values under the null hypothesis that the factor model performs worse than the benchmark models indicated in the first column. * p<0.1 ; **p<0.05 ; ***p<0.01*

6 Economic Interpretation

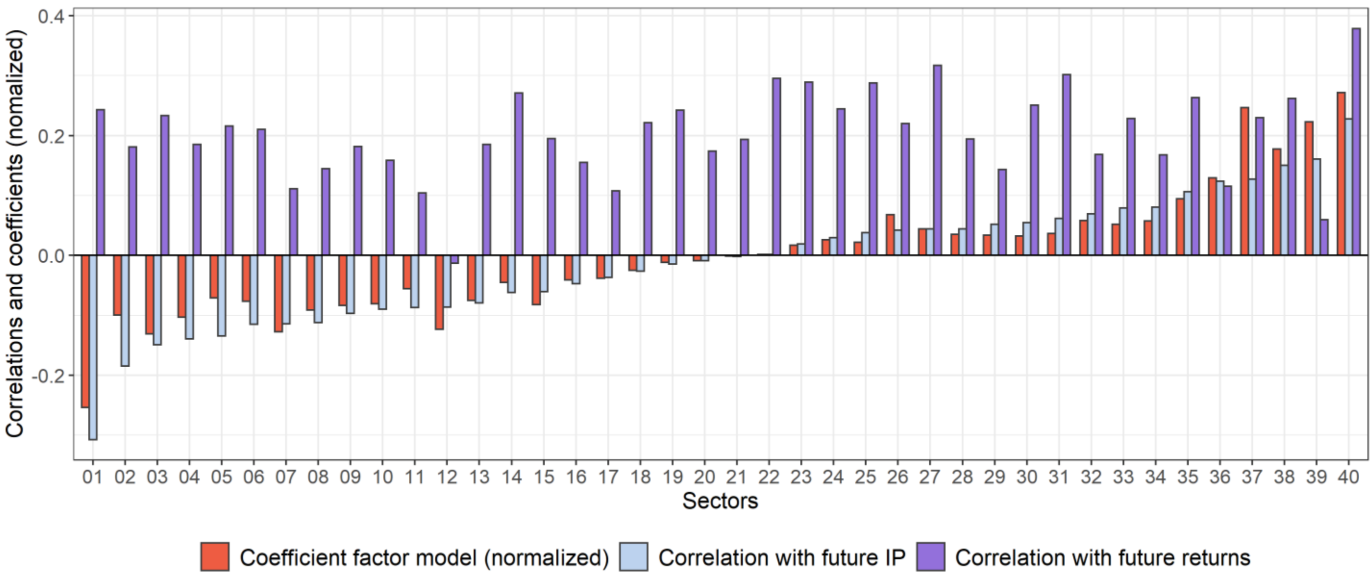
6.1 Filtering the "return" and the "foreign cash flow" components

In some ways, it should be unsurprising that predictions based on factors extracted from the cross section of sectoral portfolio variables should outperform predictions based on an aggregate variable, given that aggregate measures average out important information, and at the same time include information not directly relevant to the variable being forecasted. The question is whether one can estimate the factors with sufficient precision that one outperforms a simple model using an aggregate index. In our case, the economically important information gleaned using our approach yields a substantial gain in prediction.

In this section, we further investigate how the results can be interpreted in economic terms. Kelly and Pruitt (2013) show that, while trying to predict future aggregate returns with disaggregated book-to-market ratios, their factor model puts *positive* weights on all sectoral book-to-market ratios, especially for "growth" portfolios (i.e. portfolios with low book-to-market ratios) which are known to be very much affected by future aggregate returns. However, some of these sectoral book-to-market ratios are positively correlated with future aggregate dividends, whereas others are negatively correlated with future aggregate dividends. Consequently, the factor, which is a weighted sum of the sectoral portfolios' book-to-market ratios, will be very positively correlated with future aggregate returns but little exposed to future aggregate dividends. Similarly, when they try to forecast future aggregate dividends, they show that their factor is very positively correlated with future aggregate dividends but little exposed to future aggregate returns.

In our analysis, we replicate this exercise to identify what is filtered out in our factor model based on disaggregated DYs. To show how we do this, we display on Figure 4 three variables. In red are represented, for each of the sectors, the weights $(\widehat{\phi}_i - \bar{\phi})$ that correspond to the relative importance of each sector in the factor estimation as outlined in Section 3.1.[5] In blue are represented the correlations of each sectoral DY with the predicted variable (IP growth, y_{t+h}) that is $corr(y_{t+h,} x_{it})$. Displayed in purple are the correlations of each sectoral DY with the aggregate equity returns compounded over the forecasting horizon (r_{t+h}), that is $corr(r_{t+h,} x_{it})$. As in Kelly and Pruitt (2013) and throughout Section 6, we perform the analysis by examining in-sample estimates of the weights $(\hat{\phi}_\iota - \bar{\phi})$, while the different correlations are computed on the overall sample. We consider here, and also for the remaining of Section 6, a forecasting exercise over a 12-month horizon. Finally, for visual purposes, we normalized the sector weights so that their cross-sectional standard deviation equals the standard deviations of the correlations between sectoral DYs and future IP growth.

Figure 4: Factor weights and DYs' correlations with future IP growth and future aggregate returns
(In-sample estimates, forecasting over a 12-month horizon)



Note: The Figure represents the estimate factor weights (in red), the correlation of sectoral DYs with future IP growth (in blue) or with future aggregate returns (in purple). For visual purposes, the sector weights are normalized so that their cross-sectional standard deviation equals the standard deviations of the correlations between sectoral DYs and future IP growth. Correlations are computed on the overall dataset, while the coefficients stem from an in-sample estimation of the factor model based on a forecast horizon of 12 months.

Figure 4 clearly highlights the fact that positive weights tend to be associated with positive correlation of the sectoral DYs with future IP growth, whereas negative portfolio weights tend to be associated with negative correlation of the sectoral DYs with future IP growth. In contrast, both positive and negative portfolio weights are associated with the positive correlations of the sectoral DYs with future aggregate returns. As a result, the estimated factor --which equals the weighted sum of the sectoral DYs-- is strongly exposed to future IP growth, but little exposed to future aggregate returns, in a fashion similar to what Kelly and Pruitt (2013) found.

A visual way to notice this filtering can be done by representing our factor, estimated in-sample, over time. We therefore depict on Figure 9 in the Appendix our factor along with the aggregate Market DY and the IP growth lead by 12 month. We can thus see on the Figure that, during the 90s, our factor appears to track relatively well the future IP growth. In contrast, the (opposite of the) aggregate DY exhibits an upward trend over the period,

5 Unlike Kelly and Pruitt (2013), for this analysis we rely on the centered weights $(\hat{\phi}_\iota - \bar{\phi})$, whereas they rely on the *uncentered* weights $\hat{\phi}_\iota$. Our approach seems more appropriate to us, given that the relationship between the sectoral DYs and the estimated factors is given precisely by the centered weights: $\hat{F}_t = \frac{1}{C}\sum_i x_{it}(\hat{\phi}_\iota - \bar{\phi})$.

probably linked with the fact that, amidst the so-called ‘‘irrational exuberance” (Shiller, 2015) of the dotcom bubble, investors were requiring very low discount rates which tended to push stock prices significantly high. As our factor model purges the discount rates/expected returns component of aggregate DY, it is less affected by this trend, and therefore spots more accurately movements in future IP growth.

Additionally, we want our factor model not only to filter out the “expected returns” component of the sectoral DYs, but to also filter out the “foreign cash flow” component. In other words, relying on the notations of Section 2.1, we would like $corr(\widehat{F_t}, \Delta cf_{D,t+j})$ to be high and $corr(\widehat{F_t}, r_{t+j})$ and $corr(\widehat{F_t}, \Delta cf_{F,t+j})$ to be low.

However, whereas we can directly observe the levels of future aggregate returns, we need to rely on a proxy to assess the correlation between our estimated factor and the aggregate foreign cash flow component. Since the latter theoretically represents the component of the sectoral DYs that reflect the foreign profitability of the US firms, we rely on the foreign industrial production indices of Grossmann et al. (2014). The index that we consider here, $IP_{F,t}$, corresponds to the level of industrial activity of advanced economies, excluding the US.

Note that US IP and $IP_{F,t}$ are of course strongly correlated. Therefore, a direct assessment whether the factor model filters out adequately the future foreign activity component of sectoral DYs with $IP_{F,t}$ is likely to give biased results precisely because the estimated factor is itself positively correlated with US IP growth. On the other hand, we would like our factor model to filter out the part of foreign activity that is orthogonal to US economic activity. To do so we first regress foreign IP growth ($IP_{F,t}$) on US IP growth (y_t):

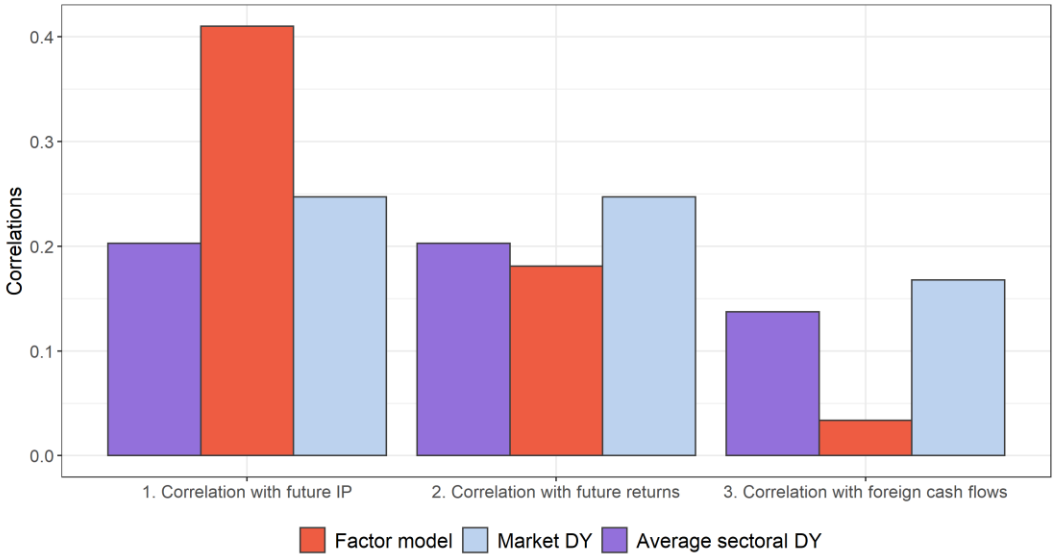
$$IP_{F,t} = \alpha + \beta y_t + u_t$$

And rely on the estimated error terms ($\hat{u}_t$) to conduct our analysis.

Figure 5 summarizes the different filterings that we consider in this section. Again, the analysis is performed here on an in-sample basis and for the 12-month prediction exercise. In red are represented the correlations of the estimated factor ($\widehat{F_t}$) with future US IP growth (y_{t+h}), with future aggregate US returns (r_{t+h}) or with the component of future foreign IP growth that is orthogonal to future US IP growth ($\hat{u}_{t+h}$). In light blue are represented the same quantities but for the aggregate DY instead of the estimated factor. Finally, in purple are pictured the average correlation of the sectoral DYs with the aforementioned variables, that is $\frac{1}{I}\sum_i corr(x_{it}, y_{t+h})$, $\frac{1}{I}\sum_i corr(x_{it}, r_{t+h})$ and $\frac{1}{I}\sum_i corr(x_{it}, y_{t+h})$.

In line with Figure 4, we can see in Figure 5 that the estimated factor is more correlated to future IP growth, and less correlated to future aggregate returns than the Market DY or than the sectoral DYs (on average). Additionally, Figure 5 also highlights that the estimated factor is clearly less correlated with the future foreign cash flow component, here proxied by our estimates $\hat{u}_{t+h}$. In other words, our factor model appears to play this role: by over/underweighting certain sectors it increases the correlation with our predicted variable while filtering out the noisy components of the sectoral DYs.

Figure 5: Factor correlations along with Sectoral and Aggregate DY correlations
(In-sample estimates, forecasting over a 12-month horizon)



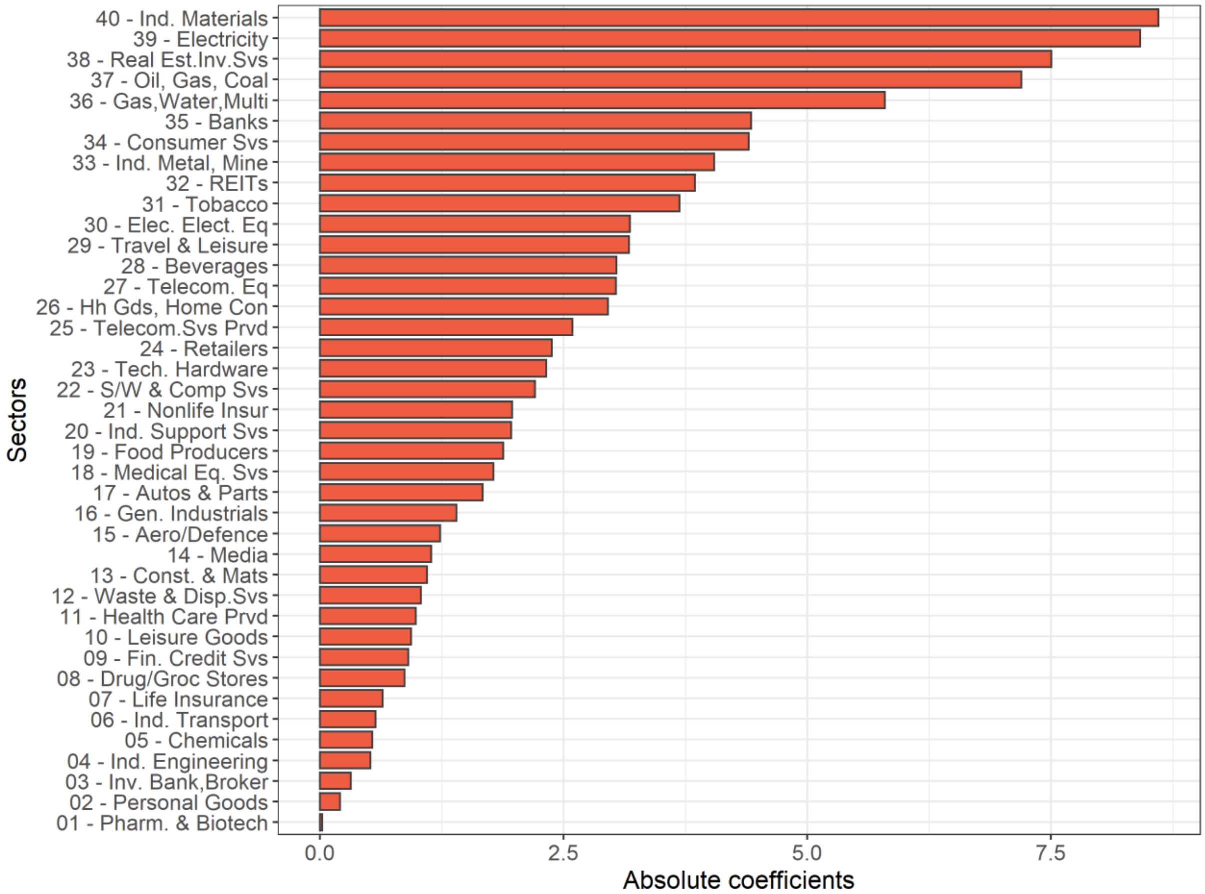
Note: On the Figure above are represented in red the correlations of the estimated factor with future US IP growth, with future aggregate US returns or with the component of future foreign IP growth that is orthogonal to future US IP growth. In light blue are represented the same quantities but for the aggregate DY instead of the estimated factor. Eventually in purple are pictured the average correlation of the sectoral DYs with the aforementioned variables. Correlations are computed on the overall dataset, while the estimated factor stems from an in-sample estimation of the factor model based on a forecast horizon of 12 months.

6.2 Sector overweighting

We investigate further the economic analysis of the outperformance of our factor model by identifying more precisely which sectors are overweighted in this exercise. To do so, in Figure 6, we depict the (absolute) weights $|(\hat{\phi}_i - \bar{\phi})|$ to understand which sectoral DYs affect the most the estimated factor. Here also we conduct this analysis on an in-sample basis, with a forecast horizon of 12 months.

Several findings emerge from inspecting Figure 6. First we notice that the factor model overweights strongly *upstream* sectors, i.e. sectors that mainly produce inputs for manufacturing and services (Oil, Gas and Coal; Industrial Materials; Electricity, Gas and Water; Industrial Metals…). Second, the factor model appears also to put more weights on industries related to the real estate sector, like Real Estate Investment Trusts (REITS) or Real Estate Investment and Services, probably due the strong link between property price dynamics and the business cycle (Leamer, 2015, Borio, Drehmann and Xia, 2020).

Figure 6: Absolute factor weights
(In-sample estimates, forecasting over a 12-month horizon)



Note: the graph represents the absolute factor weights $\left|(\hat{\phi}_\iota - \bar{\phi})\right|$, *estimated in an in-sample forecasting exercise over a 12-month horizon.*

We further investigate which sectors appear to have the more importance in our factor model by testing two additional hypotheses:

- Are “value” sectors, i.e. sectors that are little valued by equity investors and therefore exhibit low Price-Earnings Ratios (PER), overweighted compared to “growth” sectors, which, in contrast, have elevated PER. Value sector equities, like the automobile sector, are sometimes deemed to be more closely linked to the future business cycle as investors may estimate that they are less able to downsize their activity in case of an incoming recession (Koijen, Lustig and van Nieuwerburgh, 2017, Xu, 2018).
- To what extent does our factor model overweight sectors whose DYs are correlated with future domestic IP growth compared to sectors with a high exposure on foreign economic activity.

To do so, we estimate the following cross-sectional regression:

$$\left|(\hat{\phi}_\iota - \bar{\phi})\right| = \alpha + \beta_1 |corr(y_{t+h}, x_{it})| + \beta_2 PER_i + \beta_3 |corr(E_t, x_{it})| + \alpha_i + u_i$$

Where $|corr(y_{t+h}, x_{it})|$ represents, for the sector i, the absolute correlation of the sectoral DY with future IP growth, PER_i stands for the average PER of the sector i on the overall period, $|corr(E_t, x_{it})|$ represents the absolute correlation of the sectoral DY with either the US real effective exchange rate, REER, retrieved from the BIS website, or with our metric of future foreign IP growth that is orthogonal to future US IP growth ($\hat{u}_{t+h}$). Finally, α_i stands for the industry fixed effects (where the 40 sectors that we are relying on are regrouped in 11 different industries in the IBC classification).

Table 5 presents the regression results. Here again, the coefficients $\left|(\hat{\phi}_i - \bar{\phi})\right|$ are from an in-sample estimation of the factor based on a 12-month horizon.

Table 5: Absolute factor weights regressions
(In-sample estimates, forecasting over a 12-month horizon)

	Dependent variable:			
	Abs. Factor coefficients			
	(1)	(2)	(3)	(4)
Abs. corr. Future IP with DYs	25.791*** (2.175)	27.352*** (1.827)	27.202*** (1.594)	27.288*** (1.577)
Average PER		−0.130*** (0.042)	−0.142*** (0.039)	−0.121*** (0.035)
Abs. corr. Exchange rate with DYs			−1.757** (0.732)	
Abs. corr. Foreign IP with DYs				−1.792** (0.873)
Constant	0.034 (0.388)	2.611*** (0.905)	3.150*** (0.838)	2.697*** (0.800)
Observations	40	40	40	40
R2	0.889	0.925	0.936	0.932
Adjusted R2	0.846	0.892	0.904	0.899
F Statistic	20.470*** (df = 11; 28)	27.832*** (df = 12; 27)	29.325*** (df = 13; 26)	27.622*** (df = 13; 26)

*Note: All regressions include industry-level fixed effects. The reported regressions are made using White heteroscedasticity-robust standard errors. * p<0.1 ; **p<0.05 ; ***p<0.01.*

We can see first in Table 5 that, by construction and in absolute terms, factor weights are strongly and positively related with the correlation between sectoral DYs and future IP growth. Second, Table 5 underlines that, in line with the hypothesis formulated above, the DYs from the value sectors seem to contain relatively more information regarding future IP growth given that lower PERs are positively associated with the factor weights in our regressions. Third, it appears that our factor significantly underweights sectors whose DYs are strongly correlated, in absolute terms, with the US REER or with our metric of foreign IP growth. This would mean that our estimated factor puts less weight on sectors with a strong exposure on foreign economic activity, so as to better spot changes in future domestic IP growth.

7 Conclusion

In this paper, we have developed a factor model based on sectorally disaggregated stock market variables that significantly outperforms other extant macroeconomic forecasting models, and in doing so, provided an explanation for why in previous studies stock market variables have proven to be less successful predictors of economic activity than other financial variables.

We attribute our model's outperformance to two attributes of our methodology. First, we show that our model over/underweights certain sectors so that the resulting factor is strongly associated with future IP growth, but is, conversely, relatively less associated with the noisy components of the sectoral DYs, namely expected returns and the foreign component of future cash flows. Second, the superior performance of our model is related to the fact that it overweights both upstream sectors (Oil and Gas, Industrial Materials etc.) and value sectors that are deemed relatively more informative regarding future IP growth.

The factor model is better able to forecast industrial production, and particularly so during periods of negative growth. As a consequence, our model has greater precision exactly at times of economic stress. For practioners (policymakers or central bankers for example) this attribute is of particular importance given that these periods are often characterized by elevated macro-uncertainty and the need for reliable business cycle predictions.

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9 Appendix

9.1 The Factor model for sectoral and aggregate DYs

We use the sectoral DYs x_{it} in a factor model instead of the aggregate DY x_t to predict future IP growth. By doing so, we are implicitly assuming that the *sectoral* DYs are indicative of future *aggregate* domestic cash flows, which are themselves a proxy for the future US economic activity. We are also assuming that the factor model is able to isolate this information while filtering the remaining noisy components in sectoral DYs.

More precisely, in line with Kelly and Pruitt (2013), we are assuming that the expectations of sectoral returns, of sectoral domestic cash flow growth and of sectoral foreign cash flow growth are linearly determined by a set of common factors $\boldsymbol{F}_t$:

$$E_t\left(r_{i,t+1}\right) = \alpha_{i,0} + \boldsymbol{\alpha}'_{i,1}\boldsymbol{F}_t + u_{i,t}$$

$$E_t\left(\Delta cf_{D,i,t+1}\right) = \beta_{i,0} + \boldsymbol{\beta}'_{i,1}\boldsymbol{F}_t + e_{i,t}$$

$$E_t\left(\Delta cf_{F,t+1}\right) = \gamma_{i,0} + \boldsymbol{\gamma}'_{i,1}\boldsymbol{F}_t + \epsilon_{i,t}$$

Where $u_{i,t}$, $e_{i,t}$ and $\epsilon_{i,t}$ are idiosyncratic and independently distributed components with $E_t\left(u_{i,t+1}\right) = E_t\left(e_{i,t+1}\right) = E_t\left(\epsilon_{i,t+1}\right) = 0$.

The expectations of aggregate variables follow similar processes, that is:

$$E_t(r_{t+1}) = \alpha_0 + \boldsymbol{\alpha}'_1\boldsymbol{F}_t + u_t$$

$$E_t(\Delta cf_{Dt+1}) = \beta_0 + \boldsymbol{\beta}'_1\boldsymbol{F}_t + e_t$$

$$E_t\left(\Delta cf_{F,t+1}\right) = \gamma_0 + \boldsymbol{\gamma}'_1\boldsymbol{F}_t + \epsilon_t$$

Finally, we assume that the factors follow an autoregressive process:

$$\boldsymbol{F}_{t+1} = \boldsymbol{\Theta}\boldsymbol{F}_t + \boldsymbol{\nu}_{\mathrm{t+1}}$$

Therefore, in line with section 2.1, we can use the Campbell and Shiller (1988) formula for sectoral DYs:

$$x_{it} = \frac{\kappa_i}{1-\rho_i} + \sum\nolimits_{j=1} \rho_i^{j-1} E_t[r_{i,t+j} - \Delta cf_{D,i,t+j} - \Delta cf_{F,i,t+j}]$$

$$\begin{aligned} &= \frac{\kappa_i}{1-\rho_i} + \sum\nolimits_{j=1} \rho_i^{j-1} E_t[\left(\alpha_{i,0} + \boldsymbol{\alpha}'_{i,1}\boldsymbol{F}_{t+j-1} + u_{i,t+j-1}\right) - \left(\beta_{i,0} + \boldsymbol{\beta}'_{i,1}\boldsymbol{F}_{t+j-1} + e_{i,t+j-1}\right) \\ &\qquad - (\gamma_{i,0} + \boldsymbol{\gamma}'_{i,1}\boldsymbol{F}_{t+j-1} + \epsilon_{i,t+j-1})] \end{aligned}$$

$$= \frac{\kappa_i + \alpha_{i,0} - \beta_{i,0} - \gamma_{i,0}}{1-\rho_i} + \sum\nolimits_{j=1} \rho_i^{j-1} E_t[\boldsymbol{i}'\boldsymbol{\Gamma}_i{}'\boldsymbol{F}_{t+j-1} + u_{i,t+j-1} - e_{i,t+j-1} - \epsilon_{i,t+j-1}]$$

$$= \frac{\kappa_i + \alpha_{i,0} - \beta_{i,0} - \gamma_{i,0}}{1 - \rho_i} + \ \boldsymbol{i}'\boldsymbol{\Gamma}_i{}'(\boldsymbol{I} - \rho_i\boldsymbol{\Theta})^{-1}\boldsymbol{F}_t + u_{i,t} - e_{i,t} - \epsilon_{i,t}$$

$$= \phi_{i,0} + \ \boldsymbol{\phi}'_{i,1}\boldsymbol{F}_t + v_{i,t}$$

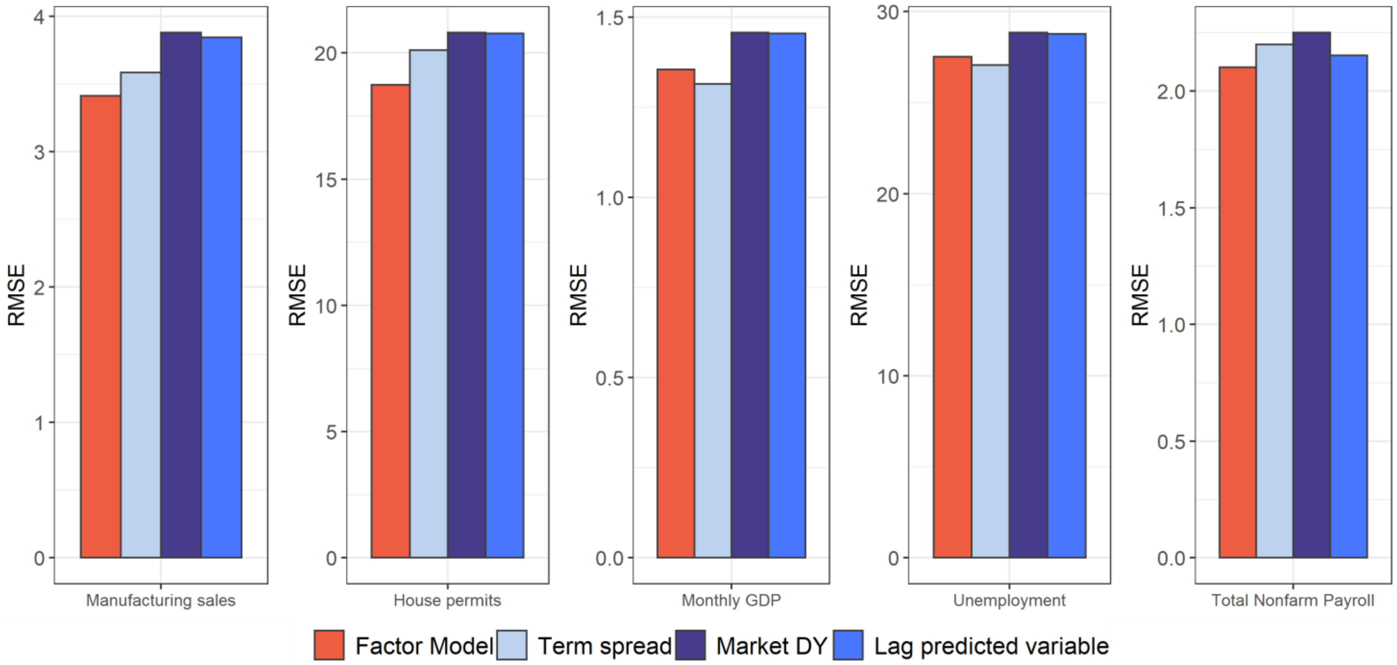
With $\phi_{i,0} = \frac{\kappa_i+\alpha_{i,0}-\beta_{i,0}-\gamma_{i,0}}{1-\rho_i}$, $\boldsymbol{\phi}'_{i,1} = \boldsymbol{i}'\boldsymbol{\Gamma}'_i(\boldsymbol{I} - \rho_i\boldsymbol{\Theta})^{-1}$, $v_{i,t} = u_{i,t} - e_{i,t} - \epsilon_{i,t}$, $\boldsymbol{i} = (1, -1, -1)'$ and

$\boldsymbol{\Gamma}_i = (\boldsymbol{\alpha}_i, \boldsymbol{\beta}_i, \boldsymbol{\gamma}_i)$.

In other words, the calculus above underlines how, by assuming that common factors affect both the expectations of sectoral and aggregate returns and cash flows, we can show that sectoral DYs are linearly related to these factors. Since the latter also affect linearly future aggregate domestic cash flows, it is therefore attractive, in this framework, to rely on the cross-section of sectoral DYs to extract a predictive signal for the future domestic cash flows.

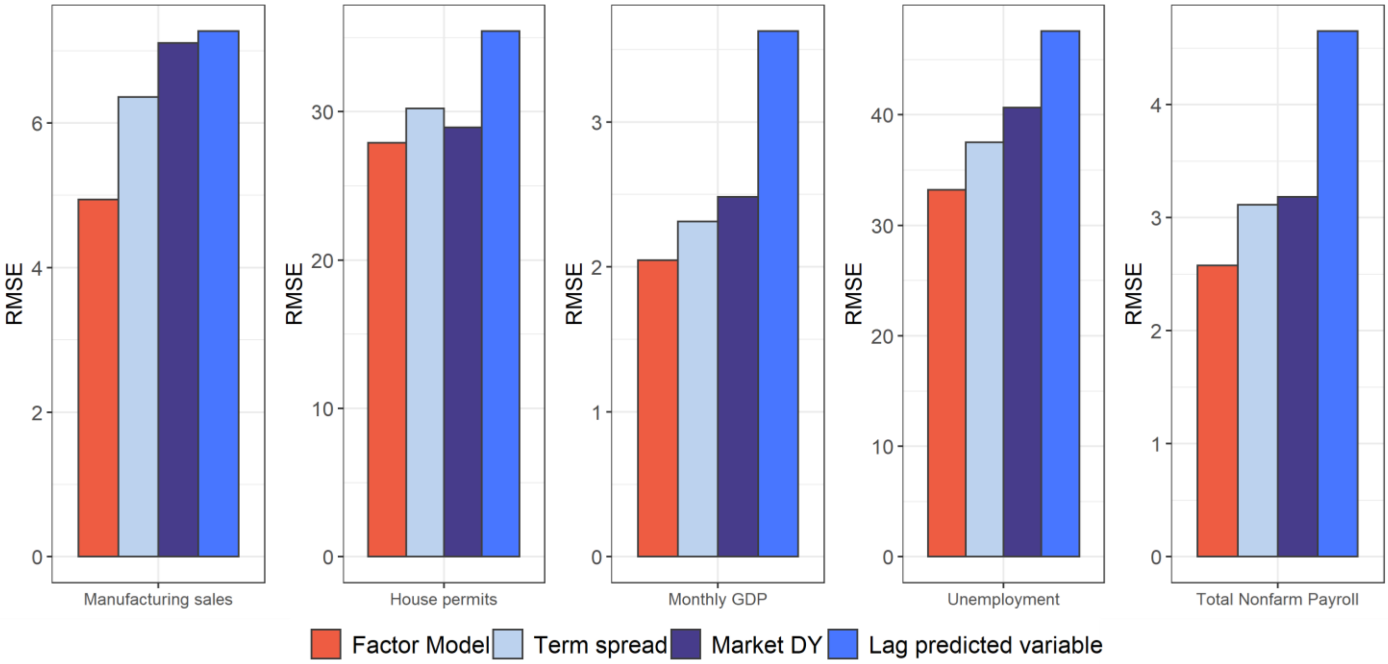
9.2 Additional forecasting results

Figure 7: Robustness check, In-Sample RMSE from the different estimated models



Note: On the graph are represented the In-Sample RMSE of different models (the factor model, or univariate regressions relying either on the aggregate DY, on the lagged IP growth or on the term spread). The predicted variables (Manufacturing sales, House permits etc.) are all defined as growth rates, similarly to the IP growth, before conducting the forecasting exercise.

Figure 8: Robustness check, Out-of-Sample RMSE from the different estimated models



Note: On the graph are represented the Out-of-Sample RMSE of different models (the factor model, or univariate regressions relying either on the aggregate DY, on the lagged IP growth or on the term spread). The predicted variables (Manufacturing sales, House permits etc.) are all defined as growth rates, similarly to the IP growth, before conducting the forecasting exercise.

Table 6: Difference in RMSE with volatility models
(Factor model – Corresponding benchmark, Out-of-sample estimates)

Benchmark:	*Horizon:*		
	12 months	*18 months*	*24 months*
Volatility 1	-4.76*	-1.57*	-9.97*
Volatility 2	-4.82*	-2.22**	-7.28**
VIX	-2.17*	-2.09**	-0.98**
MOVE	-1.69*	-2.26*	-2.81**
Volatility 1 + Term spread	-3.69**	-3.27*	-10.46**
Volatility 2 + Term spread	-3.76**	-2.94*	-8.07**
VIX + Term spread	-3.67**	-3.27**	-2.89**
MOVE + Term spread	-2.74**	-4.06*	-5.09**

*Note: The table reports the difference in RMSE of the factor model compared to the different benchmarks (a negative value means that the factor model outperforms the corresponding benchmark in terms of RMSE). The benchmarks used in this exercise are univariate or bivariate regressions relying on a market volatility variable augmented with the term spread for the last four models. The volatility metrics are: the monthly variance of daily log returns on the US stock market, Volatility 1, the monthly sum of daily squared returns on the US stock market, à la Goyal and Welch (2008), Volatility 2, the VIX and the Merrill Lynch Option Volatility Expectations, or MOVE, a metric of bond market volatility. Stars represent the Diebold-Mariano test p-values under the null hypothesis that the factor model performs worse than the benchmark models indicated in the first column. * p<0.1 ; **p<0.05 ; ***p<0.01*

Table 7: Difference in RMSE by country
(Factor model – Corresponding benchmark, Out-of-sample estimates, 12-month horizon)

Benchmark:	*Canada*	*France*	*Germany*	*Switzerland*	*United Kingdom*
Market DY	-2.13*	-3.14*	-1.27***	-5.17*	-1.5***
Term spread	-3.03*	0.16	-1.69***	-1.46***	-1.26*
Lagged IP growth	-4.2**	-0.08	-7.62*	-4.44**	-0.11
Number of sectors	21	28	24	30	38

*Note: The table reports the difference in RMSE of the factor model compared to the different benchmarks (a negative value means that the factor model outperforms the corresponding benchmark in terms of RMSE). In the same line as for our main specification (for the United States), we filter from this exercise IBC sectoral DY series that were incomplete over the time period. As a result, the number of sectors used in this analysis may differ between the different countries. Stars represent the Diebold-Mariano test p-values under the null hypothesis that the factor model performs worse than the benchmark models indicated in the first column. * p<0.1 ; **p<0.05 ; ***p<0.01*

9.3 Dataset - traditional factor model

Table 8: List of the variables used to estimate PCA-factors

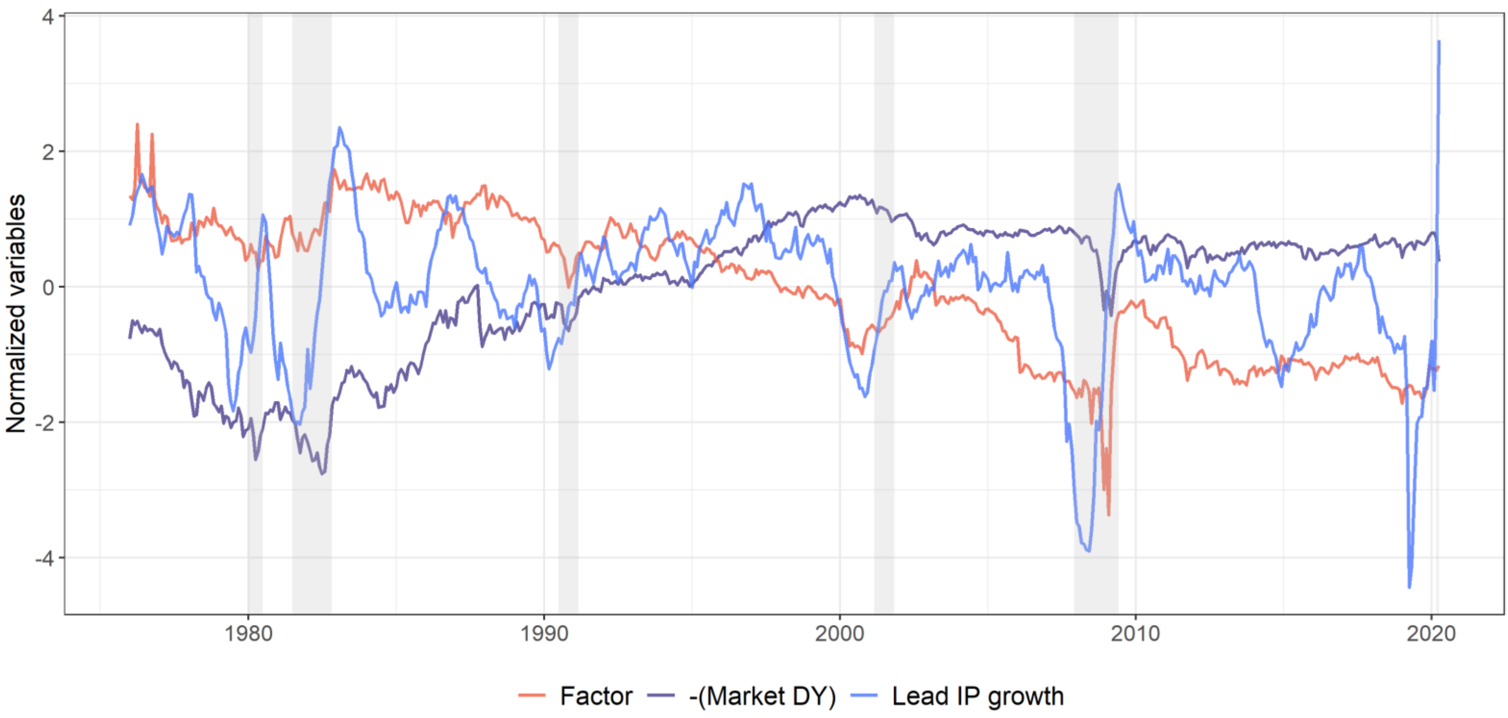
Group	*Variable*	*Source*
Consumer Price Index	CPI: All items	US BLS
Consumer Price Index	CPI: Food	US BLS
Consumer Price Index	CPI: Food at home	US BLS
Consumer Price Index	CPI: Cereals and bakery products	US BLS
Consumer Price Index	CPI: Meats, poultry, fish, and eggs	US BLS
Consumer Price Index	CPI: Dairy and related products	US BLS
Consumer Price Index	CPI: Fruits and vegetables	US BLS
Consumer Price Index	CPI: Nonalcoholic beverages and beverage materials	US BLS
Consumer Price Index	CPI: Other food at home	US BLS
Consumer Price Index	CPI: Food away from home	US BLS
Consumer Price Index	CPI: Energy	US BLS
Consumer Price Index	CPI: Energy commodities	US BLS
Consumer Price Index	CPI: Fuel oil	US BLS
Consumer Price Index	CPI: Motor fuel	US BLS
Consumer Price Index	CPI: Gasoline (all types)	US BLS
Consumer Price Index	CPI: Energy services	US BLS
Consumer Price Index	CPI: Electricity	US BLS
Consumer Price Index	CPI: Utility (piped) gas service	US BLS
Consumer Price Index	CPI: All items less food and energy	US BLS
Consumer Price Index	CPI: Commodities less food and energy commodities	US BLS
Consumer Price Index	CPI: Apparel	US BLS
Consumer Price Index	CPI: New vehicles	US BLS
Consumer Price Index	CPI: Used cars and trucks	US BLS
Consumer Price Index	CPI: Medical care commodities	US BLS
Consumer Price Index	CPI: Alcoholic beverages	US BLS
Consumer Price Index	CPI: Tobacco and smoking products	US BLS
Consumer Price Index	CPI: Services less energy services	US BLS
Consumer Price Index	CPI: Shelter	US BLS
Consumer Price Index	CPI: Rent of primary residence	US BLS
Consumer Price Index	CPI: Owners' equivalent rent of residences	US BLS
Consumer Price Index	CPI: Medical care services	US BLS
Consumer Price Index	CPI: Physicians' services	US BLS
Consumer Price Index	CPI: Hospital services	US BLS
Consumer Price Index	CPI: Transportation services	US BLS
Consumer Price Index	CPI: Motor vehicle maintenance and repair	US BLS
Consumer Price Index	CPI: Motor vehicle insurance	US BLS
Consumer Price Index	CPI: Airline fares	US BLS
Equity market	S&P 500 Dividend yield	S&P Dow Jones Indices LLC
Equity market	Dow Jones Dividend yield	S&P Dow Jones Indices LLC
Equity market	US stock market Dividend yield	Refinitiv Datastream
Equity market	US stock market Price earnings ratio	Refinitiv Datastream
Equity market	US stock market Earnings	Refinitiv Datastream
Equity market	US stock market Volatility	Refinitiv Datastream
Equity market	US stock market Log-returns	Refinitiv Datastream
Equity market	S&P 500 Excess CAPE yield	Robert Shiller website
Equity market	S&P 500 Price Index	Refinitiv Datastream
Equity market	S&P 500 Cyclically Adjusted Price earnings ratio	Robert Shiller website
Equity market	S&P 500 CAPE Ratio	Refinitiv Datastream
Equity market	Fama-French Small-minus-Big Factor	Kenneth French website
Equity market	Fama-French High-minus-Low Factor	Kenneth French website
Exchange rate	Real Effective Exchange Rates Based on Manufacturing Consumer Price Index for the US	OECD
Exchange rate	Nominal Effective Exchange Rates Based on Manufacturing Consumer Price Index for the US	OECD
Exchange rate	Echange rate EURUSD	Federal Reserve Board
Exchange rate	Echange rate JPYUSD	Federal Reserve Board
Exchange rate	Echange rate CHFUSD	Federal Reserve Board
Exchange rate	Echange rate GBPUSD	Federal Reserve Board
Exchange rate	Echange rate Australian dollar USD	Federal Reserve Board

Exchange rate	Echange rate Swiss FRanc USD	Federal Reserve Board
Household statistics	US Real Disposable Personal Income	US BEA
Household statistics	US Personal Saving Rate	US BEA
Housing statistics	Revolving Home Equity Loans, All Commercial Banks	Federal Reserve Board
Housing statistics	Revolving Home Equity Loans, Small Domestically Commercial Banks	Federal Reserve Board
Housing statistics	Housing Starts: Total: New Privately Owned Housing Units Started	U.S. Census Bureau
Housing statistics	S&P/Case-Shiller U.S. National Home Price Index	S&P Dow Jones Indices LLC
Housing statistics	Housing Starts: Total: New Privately Owned Housing Units Started	U.S. Census Bureau
Housing statistics	Supply of Houses in the United State	U.S. Census Bureau
Housing statistics	New Private Housing Units Authorized by Building Permits	U.S. Census Bureau
Housing statistics	New One Family Houses Sold: United States	U.S. Census Bureau
Housing statistics	Median Sales Price for New Houses Sold in the United State	U.S. Census Bureau
Interest rate	Ted Spread	FED Saint Louis
Interest rate	10 Year US government rate	Federal Reserve Board
Interest rate	US Bank Prime Loan Rate	Federal Reserve Board
Interest rate	Federal funds rate	Federal Reserve Board
Interest rate	Term Spread	Refinitiv Datastream
Interest rate	Moody's Seasoned Aaa Corporate Bond Yield	FED Saint Louis
Interest rate	Moody's Seasoned Baa Corporate Bond Yield	FED Saint Louis
Interest rate	Baa-Aaa Bond Spread	FED Saint Louis
IP Index	Industrial Production: Manufacturing (SIC)	Federal Reserve Board
IP Index	Industrial Production: Mining : crude oil	Federal Reserve Board
IP Index	Industrial Production: durable goods : ow steel	Federal Reserve Board
IP Index	Industrial Production: durable manuf : vehicle	Federal Reserve Board
IP Index	Industrial Production: mining : gold and silver	Federal Reserve Board
IP Index	Industrial Production: mining	Federal Reserve Board
IP Index	Industrial Production: consummer good	Federal Reserve Board
IP Index	Industrial Production: durable consummer good	Federal Reserve Board
IP Index	Industrial Production: non durable manuf : food alcool beverage	Federal Reserve Board
IP Index	Industrial Production: durable manuf : machinery	Federal Reserve Board
IP Index	Industrial Production: business equipement	Federal Reserve Board
IP Index	Industrial Production: non durable manuf : chimestrey	Federal Reserve Board
IP Index	Industrial Production: durable manuf : computer	Federal Reserve Board
IP Index	Industrial Production: Material	Federal Reserve Board
IP Index	Industrial Production: consruction supplies	Federal Reserve Board
IP Index	Industrial Production: Mining :oil & gas extraction	Federal Reserve Board
IP Index	Industrial Production: Non durable consummer good	Federal Reserve Board
IP Index	Industrial Production: Durable manufacturing: Electrical equipment, appliance, and component	Federal Reserve Board
IP Index	Industrial Production: Durable manufacturing: Aerospace	Federal Reserve Board
IP Index	Industrial Production: Durable manufacturing:	Federal Reserve Board
IP Index	Industrial Production: Non Durable manufacturing	Federal Reserve Board
IP Index	Industrial Production: Business supplies	Federal Reserve Board
IP Index	Industrial Production: IPI hors energy (74%)	Federal Reserve Board
IP Index	Industrial Production: Durable material	Federal Reserve Board
IP Index	Industrial Production: Non Durable material	Federal Reserve Board
IP Index	Industrial Production: Industrial equipment	Federal Reserve Board
IP Index	Industrial Production: manufacturing exluding vehicle	Federal Reserve Board
IP Index	Industrial Production: SA equipment total	Federal Reserve Board
IP Index	Industrial Production: electric & gas utilities	Federal Reserve Board
IP Index	Industrial Production: Total Index	FED Saint Louis
Labor statistics	Unemployed level, thousands	US BLS
Labor statistics	Employment level, thousands	US BLS
Labor statistics	US employment rate: Age 25 to 54	OECD
Labor statistics	Employment population ratio	US BLS
Labor statistics	All Employees: Total Nonfarm	US BLS
Labor statistics	US unemployment rate	US BLS
Labor statistics	Continued Claims (Insured Unemployment)	U.S. ETA
Leading Indicator	Chicago Fed National Activity Index	FED Saint Louis
Leading Indicator	Future New Orders; Diffusion Index for FRB - Philadelphia District	FED Philadelphia
Leading Indicator	Orders: Manufacturing: Total orders: Value for the United States	OECD
Leading Indicator	Manufacturers' New Orders for All Manufacturing Industries	U.S. Census Bureau
Leading Indicator	Manufacturers' New Orders durable goods	U.S. Census Bureau
Leading Indicator	Advance Real Retail and Food Services Sales	FED Saint Louis
Leading Indicator	Advance Retail Sales: Retail (Excluding Food Services)	FED Saint Louis
Leading Indicator	Advance Retail Sales: Retail and Food Services, Total	FED Saint Louis

Leading Indicator	Advance Retail Sales: Building Materials, Garden Equipment and Supplies Dealers	FED Saint Louis
Leading Indicator	Advance Retail Sales: Clothing and Clothing Accessory Stores	FED Saint Louis
Leading Indicator	Advance Retail Sales: Food Services and Drinking Places	FED Saint Louis
Leading Indicator	Advance Retail Sales: Furniture and Home Furnishings Stores	FED Saint Louis
Leading Indicator	Advance Retail Sales: Retail and Food Services Excluding Motor Vehicles and Parts Dealers	FED Saint Louis
Leading Indicator	Advance Retail Sales: Gasoline Stations	FED Saint Louis
Leading Indicator	Advance Retail Sales: Electronics and Appliance Stores	FED Saint Louis
Leading Indicator	Advance Retail Sales: Auto and Other Motor Vehicle	FED Saint Louis
Leading Indicator	Advance Retail Sales: Nonstore Retailers	FED Saint Louis
Leading Indicator	Advance Retail Sales: Motor Vehicle and Parts Dealers	FED Saint Louis
Leading Indicator	Advance Retail Sales: Food and Beverage Store	FED Saint Louis
Leading Indicator	Advance Retail Sales: Sporting Goods, Hobby, Book, and Music Stores	FED Saint Louis
Leading Indicator	Advance Retail Sales: Health and Personal Care Stores	FED Saint Louis
Leading Indicator	Advance Retail Sales: Retail Trade and Food Services, Excluding Motor Vehicle and Gasoline Station	FED Saint Louis
Leading Indicator	Advance Retail Sales: Retail Trade and Food Services, Excluding Gasoline Stations	FED Saint Louis
Leading Indicator	Leading Indicators OECD: Component series: CS - Confidence indicator	OECD
Surveys	Business Surveys: Order Books: Level	OECD
Surveys	Business Surveys: Export Order Books or Demand	OECD
Surveys	Business Surveys: Confidence Indicators (OECD)	OECD
Surveys	Business Surveys: Capacity Utilization	OECD
Surveys	Business Surveys: Confidence Indicators (European Commission)	OECD
Surveys	Business Surveys: Orders Inflow	OECD
Surveys	Business Surveys: Production	OECD
Surveys	Consumer Opinion Surveys: Confidence Indicators	OECD

9.4 Estimated factor

Figure 9: Estimated Factor, Market DY and Lead IP growth
(In-sample estimates, forecasting over a 12-month horizon)



Note: The Figure represents the estimated factor (in red) based on an in-sample forecasting exercise over a 12-month horizon, the Market DY (in purple) as well as the IP growth lead by 12 month. For visual purposes we represent here the opposite of the Market DY and we normalized the three variables.