Forecasting of Important Economic Indicators based on Mobile Data and its application to effective trading[1]

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Abstract.

In this paper, we propose effective forecasting method of important economic indicators by utilizing mobile data and show its application to effective trading. There are so many articles about economic indicators forecasting models and researchers tried to create them based on historical data (time series data). Their methodologies are multivariate regression or autoregression models. Our approach is completely different from them because of our utilizing mobile data and not using historical data. More specifically, we count the number of mobile phone users, who permitted us to analyse, mesh by mesh mobile spatial statistics (MSS) and utilized these statistics to estimate operating status of production area. This approach enables us to stably forecast even when its trend suddenly changed from the historical data. In this paper, we focus on Japan's production index which is one of the most important indexes to well predict Japan's GDP (Gross Domestic Product) and its growth rate. Production index can explain around 20% of Japan's GDP also can explain 40% if it includes closely related industries. Many investors/economists/analysts are forecasting production index for market participants' effective trading and investors are reallocating their trading portfolio accordingly. Production index is reported monthly by government[2]. Preliminary report is released after one month (Ex. Production index in January is reported around the end of March) and Confirmation report is released after two months (around the end of April). Our approach enables us to forecast after a few days (Ex. Production index in January can be checked around February 3rd). In this paper, we mainly explain how to utilize MSS for forecasting production index and show numerical result (The correlation between GDP and our forecast was greater than 0.83) also introduce how to utilize them for effective trading.

Keywords: Big data, GDP prediction model, Mobile Spatial Statistics, Production Index

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[2] Ministry of Economiy, Trade and Industry (https://www.meti.go.jp)

1. Introduction

GDP is one of the important economics indexes all over the world and many researchers including economist and strategists at banking sector are trying to forecast it. Also, asset pricing model has two factors, one is macro factor and the other one is micro factor. The former is called as market factor and the later is idiosyncratic factor. GDP is utilized as one of effective parameters as market factor and embedded in the asset pricing models. To predict GDP accurately, Production index is one of the most powerful indexes in Japan. Because it is said that Production index in Japan reflects large weight of Japan's economic activities. The index explains around 20% of Japan's GDP and 40% of Japan's GDP when it includes close related industries. Additionally, it sensitively reflects economic and business situation in Japan. If the area (country) is having good timing of business cycle, there are strong demand and as a result production index will be high. Elseif the area (country) is having bad timing of business cycle, there are excessive product stock, and we will see weak demand. Then production index is low.

There are many papers which challenged to forecast production index. They are two types: multivariate regression or autoregression models based on the historical data like (Marchetti et al. 2000), (Bruno et al. 2000), (Mohsen et al. 2015), and (Zizza 2002). They might work to some extent under stable situation but will not work under unstable situation like our current situation: Covid-19 which changed our economic trend suddenly/dramatically. If you carefully create forecasting model of production index based on historical data, it's almost impossible to predict Covid-19 situation: namely production index's sharp down due not only to developed countries' turmoil but also to supply chain suspension especially hitting in Asian developing countries.

In this paper, we do not utilize historical data, seasonal data, and/or cyclical trend but utilize mobile data for forecasting production index. The idea is quite simple. We count the number of mobile phone signals, which permitted us to observe, inside target area. We set industrial zone as target observing area in this paper. Similar research was proposed in (Kaneko et al. 2022). They utilized mobile data for effective trading of specific financial product. They applied mobile data to J-REIT which owns commercial real estates and pay dividend to shareholders like companies. Interesting point is that J-REITs are exempted from paying corporate tax (corporate tax rate is around 23% in Japan) on condition that they pay out more than 90% profit to their shareholders. Then J-REITs systematically have high correlation between their revenue and dividend as a result share price. To forecast revenue, namely operation rate of real estate, the researchers observed the number of mobile phone signals. We take similar approach. Future more, Production index could be seen as being influential on product prices due to manufacturers launch their production when there is strong demand for their products and stop or slow down their production when there is weak demand for their products. Under the former situation, product prices tend to go up (inflation) and under the later situation, product prices tend to go down (deflation). This implies that production index analysis can be utilized for analysing/forecasting consumer product price index (CPI). This will be included in our future work. In the next chapter, we explain our model and numerical experiments, after that we write conclusion with our future works.

2. Model and Numerical experiments

As preparation, we use the idea that annual salaries for labours in production area are not widely distributed. As you can see below Figure 1, blue line indicates annual salaries by ages for labours in production area in Japan, while red line indicates annual salaries by ages for managements/office workers in production industries in Japan. Blue line is stable (flat) more than red line. If annual salaries widely distribute like red line, we need to estimate each salary and age band for observed signals. But it does not distribute so, this characteristic enables us to regard almost same salary for each observed signals in production area.

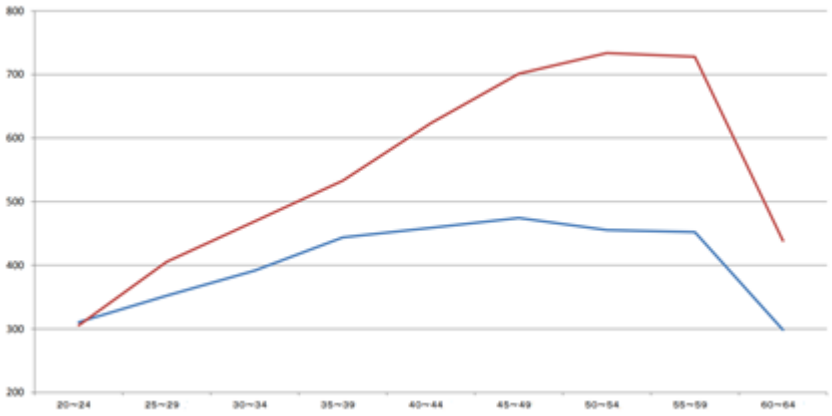

Fig. 1 Annual salaries by age of production industries in Japan. Vertical axis indicates annual salary (×10,000Yen) and horizontal axis indicates ages. Blue line indicates annual salaries for labours in production sites and red line indicates annual salaries by age for management/office workers in the same industries. We obtained this figure from below government website and put slight modification on captions.

(https://www.mhlw.go.jp/stf/shingi/2r9852000002790h-att/2r98520000027bof.pdf)

As above, annual salary of labours in production area is not widely distributed then we put assumption that their salary is almost same. Companies in production industry are adjusting the number of labours to be consistent with their budget constraint. For example, they hire many labours when they have strong demand or high profitability of their products. Else if they do not have strong demand or high profitability, they have tight budget constraint and start to decrease their number of labours in their production area. That is why we supposed that there is strong positive correlation between the numbers of labours in production area and financial situation more specifically gross profit margin of manufacturing industry. We propose to forecast productions industry's profitability which is tightly correlated with production index by monitoring the number of labours in the production area. We count the number of smart phone signals, which permitted us to observe their location, for forecasting Production index in Japan. See figure 2.

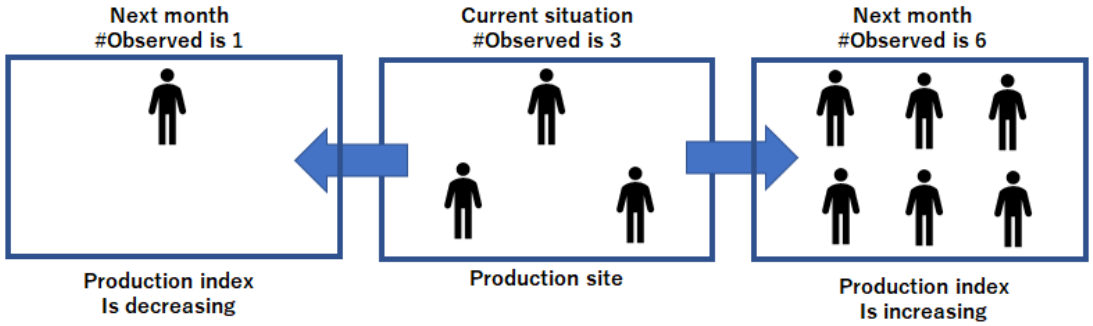

Fig. 2 Image of observing number of smart phone signals in the target production site to estimate production index. Left case indicates production index decreases due to #Observed signals decreases. While right case indicates production index increases.

To set observing production area, we can technically monitor all large manufacturing companies' production areas. But it takes very long time to prepare then it's not productive, also it has necessity to check current usage accordingly so it's not practical. In this paper, we decided to observe three largest industrial zones in Japan. They could include irrelevant places: shops, houses, public roads and so on. The number of signals observed in these irrelevant areas is stable and automatically ignored when we focus only on changes of the number of signals.

As the three largest production areas, we use Keihin industrial zone (around Tokyo), Hanshin industrial zone (around Osaka), and Chukyo industrial zone (around Nagoya) as below figure 3.

zone. Grey areas in above figures are to be observed in the following numerical experiments. ©OpenStreetMap contributors

In the numerical experiments, we aggregated daily number of observed signals to be monthly format and compare them with official production index released by government as below figure 4. The correlation between official production index and observed signals is greater than 0.83. As benchmark to be compared, we randomly created observing areas which have same space and calculated correlations after checking the number of signals. The average of correlations was around 0.363. Additionally, we are observing more sound correlation under Covid-19 situation which suddenly changed economic trend including operation of production industry. We think that similar phenomenon can be seen all over the world.

Fig.4 Production index in Japan and the number of observed monthly signals in the three larges industrial zones. The vertical axis on the right indicates index level of the number of observed smart phone signals in the target zones. The vertical axis on the left indicates the level of production index. The horizontal axis indicates time: from 2017 Oct to 2020 Apr.

3. Conclusion and future works

In this paper, we proposed new idea to forecast production index by utilizing the number of observed smart phones. And our numerical experiments say that there are strong relationship. This idea enables us to check current producing situation quickly and quicker than preliminary official report released by government. Above correlation was calculated based on the numbers in confirmation report released after two months. These characteristics (accuracy and speediness) make us possible to predict markets' moving direction especially when the market surprises (Market surprise) happen. They happen just after when the market consensus of important economic indexes like production index are noticed as being far from the actual numbers and investors need to suddenly change/adjust their portfolio/positions to be consistent with actual economic indices. Because almost all investors are utilizing important economic factors to decide their selling or buying securities and adjusting their portfolio allocation. We know the market direction just after the official report released and can utilize this opportunity for effective trading due to our having enough time to prepare. We are planning to have numerical experiments based on historical market surprises. Additionally, we are preparing to investigate relationship between product price (CPI) and production index. Because we think that strong production will be seen in industrial zones under strong product demand also weak production will be seen under weak demand.

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