If trade marks lead business confidence in Australia, can it be forecast reliably?

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Identifying leading indicators of business cycles is a topic of pronounced interest to financial, macroeconomic and public sector economists. Identifying the leading indicators of trade mark applications is similarly a topic of pronounced resource-allocation interest to intellectual property offices, including IP Australia. This paper attempts to answer the question of whether trade marks lead economic indicators, in the Australian context, using methods adapted from the finance literature. In answering this question, this paper then presents a method to forecast trade mark applications in a manner useful to an examining office.

Trade marks and economic activity

This paper addresses itself to the equivocal evidence on whether trade mark applications are correlated with economic activity (Luini and Mangani 2004; Fink, Javorcik and Spatareanu 2005), and if so, whether they lead economic indicators (Yorukoglu 2000, Bock et al 2004). There is no agreed theoretical model as to why trade marks should relate to economic activity, although some authors consider it a measure of product diversity (Broda and Weinstein 2006; Melitz and Ghironi 2007) or a proxy for the introduction of new products or companies into the economy (Devinney 1990, Mendonca; Pereira, & Godinho 2004).

A second strand of literature considers trade marks to be assets which are relatively inexpensive and easy to acquire, but which can be the basis for larger investments into brands (e.g. Goodridge, Haskel and Wallis 2014). Given that trade marks can be one of a firm's most important intangible assets, authors have looked at how trade marks impact on firm valuation and export performance (WIPO 2013, Ang, Madsen, & Robertson 2015), but have not yet agreed a theoretical basis for linking trade mark activity to economic activity.

Given the absence of a theoretical foundation, we apply Principal Component Analysis (PCA), adopted from finance and monetary policy, to provide an a-theoretical exploration of the leading and lagging indicators around trade mark applications (e.g. Machado et al 2001, Favero, Marcellino and Neglia 2005). This method allows us to explore the correlations between a range of economic variables and trade mark application.

The paper uses Australian data for quarterly trade mark applications between 1980 and 2016 in combination with a broad set of macroeconomic variables ranging from investment and GDP, through confidence measures, profits, wages, and composite leading indicators (noted in appendix A). Preliminary results indicate that Australian trade mark applications are a good leading indicator of business confidence. This suggests that trade mark filings are highly pro-cyclical in nature, which is consistent with findings in the literature (e.g. Axarloglou 2005). Given this initial result, the forecasting of trade mark applications is complicated by the lack of good leading indicators to precede trade marks.

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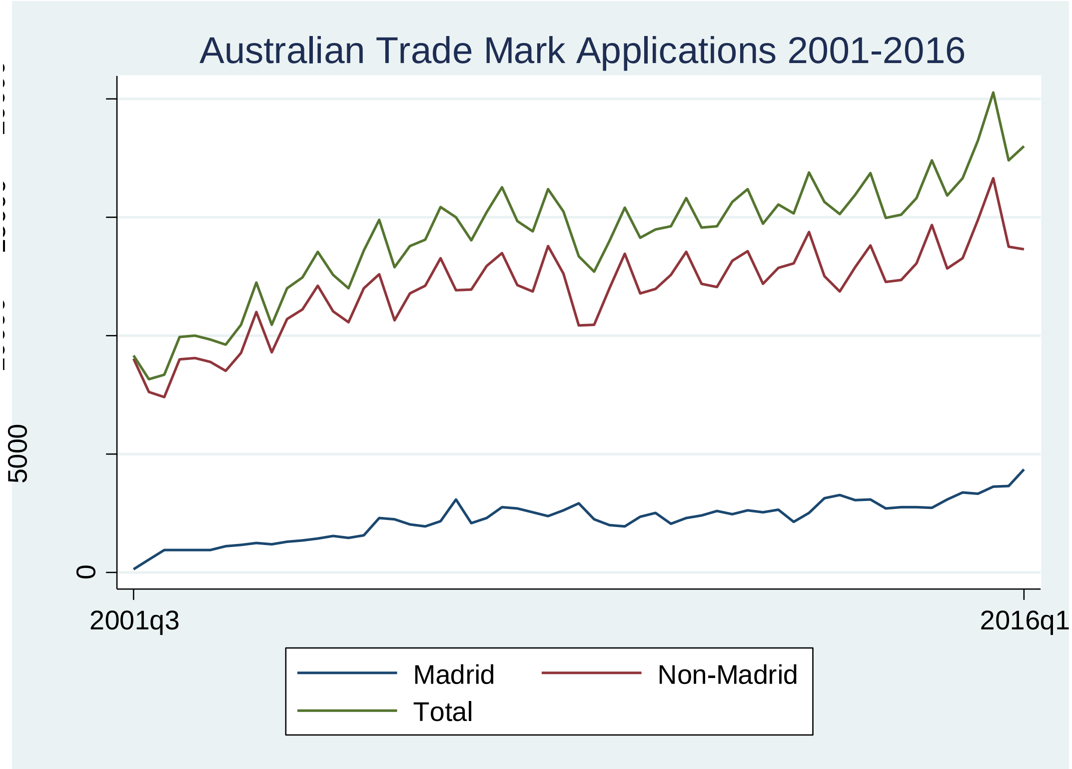
Forecasting trade mark applications

While there has been substantial literature surrounding models predicting patent filings, there is less work in the area of trade mark forecasting (Hidalgo and Gabaly 2012), and less still in the Australian context. Trade mark filings display several important features: There is a marked difference between domestic and international applications, strong seasonal influences and upward trends (see Figure 1).

Figure 1: Trade mark applications in Australia, quarterly



The few published papers which attempt to build trade mark forecast models, have equally found no empirically useful indicators, as noted by Bock et al (2004) in their study on Swiss applications, and Hidalgo and Gabaly (2012) in their study of Spanish applications.

Hidalgo and Gabaly (2012) further provide an overview of forecasting techniques used by IP offices to predict patent, trade mark and design applications, noting the diversity, and lack of leading indicators for trade marks. Traditional methods include trend extrapolation, exponential smoothing, as well as auto-regressive and ARIMA family techniques. Some offices also involve the use of non-quantitative techniques, such as surveying IP experts or users. While Bock et al (2004) use a state-space model to forecast trade marks – with an 11% in-sample error – Hidalgo and Gabaly (2012) offer three modelling exercises which predict annual applications: 1. Exponential smoothing model (Holt type), 2. an Auto-regressive model of order 1 (AR1) and 3. an ARIMA model, with the preferred (1,1,0) specification.

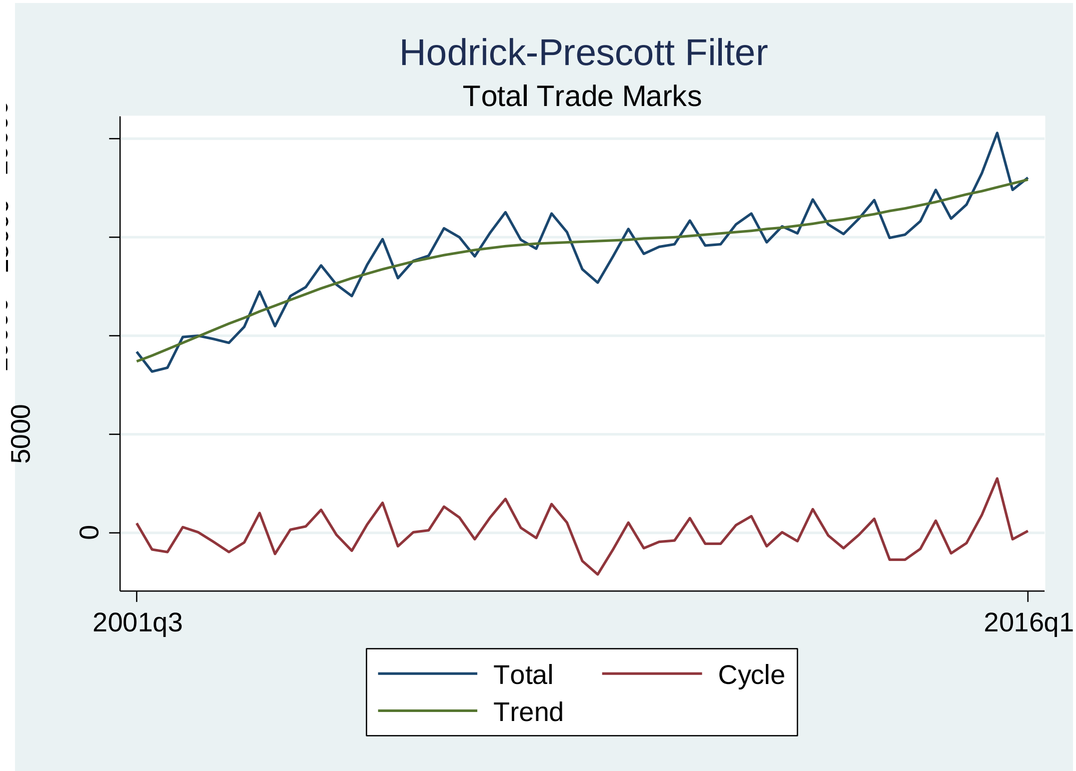
We follow a similar approach to Hidalgo and Gabaly (2012) in that we test an AR model, and extend that to an ARIMA model which we test in and out of sample. The historical series of Australian trade mark data vastly differs from the Spanish trade mark data series both in length and structure. Further, we wish to forecast Australian trade mark applications on a quarterly basis rather than annually, which will involve directly dealing with seasonality.

Estimation

We use the Hodrick-Prescott (HP) filter to separate the cyclical component of a time series from raw data to obtain smoothed curve representation of time series which is more sensitive to long term than to short term fluctuations. Applying the HP filter confirms the heavy cyclical component of the series. We seasonally adjust Madrid, Non-Madrid and Total trade mark applications using the US Census Bureau's X-13 seasonal adjustment tool.

Madrid and National trade mark applications appear to be similar but distinct processes. National applications exhibit greater policy sensitivity and volatility than the more consistent and trend-linked Madrid applications, see figure 2.

Figure 2: Hodrick-Prescott Filter applied to Total trade marks series



In testing the results, we have found that the autocorrelation function decays slowly towards zero, whereas the partial autocorrelation function only displays one significant peak in the first delay. These results indicate the series is not stationary, meaning an ARIMA (p,d,q) model may be more appropriate than an AR model. This also leads us to conduct *Augmented Dickey Fuller* (ADF) and *Kwiatkowski-Phillips-Schmidt-Shin* (KPSS) tests which indicates the series is difference-stationary, leading us to include d=1 in an ARIMA model. While the preliminary evidence suggests an ARIMA model is more appropriate, we include estimations of AR models to compare forecast performance, but our initial results suggests an ARIMA(4,1,1) model is able to successfully predict trade mark applications out-of-sample to a high degree of accuracy.

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Appendix A: Variables

Variable (quarterly, 1980-2016)	n	Mean	Std. Dev.	Min	Max
Madrid route trade mark applications	59	2,240.00	843.00	132.00	4,346.00
Non-Madrid trade mark applications	59	11,965.00	1,821.00	7,421.00	16,646.00
Total number of trade mark applications	59	14,206.00	2,535.00	8,170.00	20,273.00
Consumer Price Index	144	68.43	23.14	25.40	108.40
Domestic Unemployment	144	6.99	1.81	4.08	11.10
Business Confidence	143	99.91	0.97	96.42	101.97
Consumer Confidence	144	99.96	1.15	96.57	102.01
Inventories Total	122	96,142.64	36,826.49	41,863.00	153,635.00
Inventories Manufacturing	127	33,526.87	11,189.67	14,909.00	52,031.00
Sales, Retail	68	72,112.63	14,182.02	47,611.00	95,082.00
Sales, Manufacturing	127	62,034.39	24,441.35	22,328.00	102,931.00
Australian Company Profit before tax	86	27,961.20	16,128.27	5,304.00	53,772.00
Wages total (current price)	60	93,467.58	22,878.84	57,070.00	127,359.00
Total number of dwelling units	130	40,302.84	6,336.82	28,974.00	59,606.00
Dow Jones Industrial Average	145	7,253.59	5,040.91	785.75	17,823.07
Gross fixed capital formation ($ mil)	144	39,186.81	26,905.24	6,622.00	91,572.00
GDP per capita change	145	233,759.70	87,959.59	122,192.00	389,130.00
OECD Composite Leading Indicators	144	100.01	1.01	96.70	102.30
Australian Dollar Trade-weighted Index	141	64.15	11.29	48.70	94.10
Bank lending to business	89	54,917.71	25,685.22	15,008.00	111,957.00
Total number of building jobs;	58	1,086.43	202.86	587.67	1,485.33
S&P 500	132	735.68	472.47	104.70	1,514.19
Business Expenditure on R&D (BERD)	80	8,784.15	5,655.95	2,862.00	18,849.00
Australian Interest rate spread	140	2.98	1.43	-0.29	5.35
Private Consumption	145	103,612.90	64,548.26	19,076.00	239,709.00