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Nowcasting Modified Domestic Demand using Monthly Indicators

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Abstract:

The COVID-19 pandemic has highlighted the need for timely information on the evolving economic impacts of such a crisis. During these periods, there is an increased need to understand the current state of the economy in order to guide the effective implementation of policy. This is made difficult by the fact that official estimates of economic indicators, such as those published in the CSO's Quarterly National Accounts (QNA), are released with a substantial lag. This working paper shows that the information contained in a large number of monthly Irish economic indicators can be related to the official statistics of the QNA, namely Modified Domestic Demand (MDD), under the methodological framework of a dynamic factor model (DFM). The paper indicates that this methodology can be applied not only to nowcast quarterly MDD, but also to compute the dynamics of Irish economic activity at a monthly level. This monthly indicator can in turn be decomposed so that the contribution of each sub-category can be examined. The paper also suggests that accounting for structural breaks improves the nowcasting performance of MDD.

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1 INTRODUCTION

Understanding the current state of the economy is important for economic analysts and policy makers because key statistics on economic activity, such as GDP and personal consumption, are published with a significant lag. According to Bańbura and Rünstler (2011), the usual lag between the end of the reference quarter and the first estimates of GDP across Eurozone economies is 6 weeks. Ireland's national accounts figures are released with an even greater lag. For example, in 2020 the CSO released the national accounts for Q3 on December 3rd (lag of 65 days or 9.3 weeks), for Q2 on September 7th (lag of 69 days or 9.9 weeks) and for Q1 on June 5th (lag of 66 days or 9.4 weeks). Additionally, national accounts are often subject to substantial revisions as more source data becomes available, as discussed for the Irish case by Bermingham (2006). Meanwhile, a large number of indicators related to economic activity tend to be released well before official national accounts are available, and typically at higher frequencies i.e. monthly. The gap between the end of a reference quarter and the release of provisional national account data means that key policy decisions are made in real time with a degree of uncertainty, given a lack of full information on the current state of the macroeconomy. As pointed out by Marcellino and Sivec (2021), nowcasting models have become increasingly important tools in mitigating against some of these uncertainties. The COVID-19 pandemic has further highlighted the critical role of both detailed and timely information, making the necessity of such nowcasts even more acute (Huber, Koop, Onorante, Pfarrhofer, & Schreiner, 2020).

The basic principle of nowcasting is the exploitation of data which is published early, and typically at higher frequencies, than the target variable of interest in order to obtain an 'early estimate' before the official figure becomes available (Bańbura, Giannone, Modugno, & Reichlin, 2013). The practice of forecasting the movements in key economic indicators before their official release using all relevant information available at the time has been widely used by forecasters at many central banks and other policy institutions for a number of years. The Federal Reserve Banks of both New York (Bok, Caratelli, Giannone, Sbordone, & Tambalotti, 2017) and Atlanta (Higgins, 2014), the European Central Bank (Angelini, Camba-Mendez, Giannone, Reichlin, & Rünstler, 2011) and (Bańbura & Rünstler, 2011), the Reserve Bank of New Zealand (Richardson, van Florenstein Mulder, & Vehbi, 2021) and Norges Bank (Aastveit & Trovik, 2012) are just a few examples of institutions who have added nowcasting to their policy and decision making toolkit in recent years.

In the Irish case, early work in the area of nowcasting macroeconomic variables can be found in D'Agostino, McQuinn, and O'Brien (2008) and later Byrne, Morley, and McQuinn (2014), both of which applied the seminal methodology devised by Giannone, Reichlin, and Small (2008) to nowcast Irish GDP. These papers suggest that nowcasting can play an important part of the suite of models used to assess the performance of the Irish economy. Using the same methodological approach, Liebermann (2011) finds that exploiting the information for the reference quarter provided by the high frequency releases helps at obtaining a more precise estimate of Irish GDP growth ahead of its official release.

While the earlier Irish nowcasting literature focused on estimating GDP in real time, Marcellino and Sivec (2021) points out that nowcasting the current economic conditions is more complex for a small open economy due to the higher volatility of its national account data. The problems that the Irish economy has experienced in interpreting its national accounts, and GDP in particular, due to the many facets of the globalisation process have been well documented[1]. As a result, one key development in this area of research post 2015 has been the departure from the traditional nowcasting of Irish GDP. Alternatively, many institutions including the ESRI, the Department of Finance, and the Central Bank of Ireland have begun to highlight Modified Domestic Demand (MDD) as the preferred measure of the domestic economy, believing it to be a more accurate barometer of underlying economic activity. Accordingly, the Central Bank of Ireland (Conefrey & Walsh, 2018) and the Department of Finance (Daly & Rehill, 2020) have both produced monthly measures of economic activity (titled a business cycle indicator (BCI) and underlying economic activity measure respectively) which can be used to nowcast macroeconomic indicators such as MDD and Underlying Domestic Demand (UDD). The Central Bank of Ireland paper finds that their estimated BCI provides a stronger indication of domestic economic activity compared to both a benchmark and employment based model while the Department of Finance's estimates also provide an accurate representation of quarterly Irish economic activity, which improves as additional data is released during the reference quarter.

The aim of this paper is to add to the body of literature on nowcasting of Irish macroeconomic variables by following two methodological steps. First, it will apply a dynamic factor model to a panel of monthly variables in order to extract a single indicator of economic activity. Secondly, it will use this indicator to nowcast Irish MDD using two standard approaches from the nowcasting literature. The remainder of the paper is structured as follows; Section 2 outlines the data and describes the panel of monthly variables used in the estimations. Section 3 outlines the dynamic factor methodology and the techniques used to link the estimated series of economic activity to MDD. Section 4 examines the results of the estimations including the dynamics of the monthly activity indicator, its relationship to other macro variables and its decomposition. This section also examines the performance of various nowcasting models. Finally, Section 5 concludes.

[1] For a detailed account of the challenges both for national accounting practices and the interpretation of the national accounts themselves see Fitzgerald (2018)

2 DATA

The first aim of this paper is to extract a single measure or indicator of Irish economic activity from a panel of monthly variables. This panel is comprised of fifty-two indicators across eight different components or blocks. This includes *Financial, Labour, Prices, Housing, Fiscal, Consumer, Output* and *Soft or Survey indicators*. As the paper is interested in relating the monthly indicators to the level of MDD rather than GDP, the model excludes variables which are less relevant to domestic economic conditions. This includes omitting variables which would reflect activities of foreign multi-nationals operating in Ireland or other globalisation related measures which have caused distortions in GDP statistics in the past. All of the indicators across the eight components are publicly available and no proprietary data is used. Table 3 (Appendix I) describes all the variables across the different components as well as their source and reference code[2]. After transformation of the raw data, each series is normalized by subtracting the mean of each and dividing by the standard deviation. Therefore, each series has a mean of 0 and a standard deviation of 1, as will the final estimated indicator.

The consumption component is mainly comprised of retail sales across several subsectors but also includes the number of new and total vehicles licensed in a given month. This not only gives an indication of the level of actual consumption in the economy but also speaks to the level of consumer confidence. The financial component is largely related to interest rate (both short and long-term) and exchange rate movements (Euro vis a vis the Dollar and Pound Sterling) as well as a measure of the Irish stock market. Prices are represented by the consumer price index (CPI) across all items and separately across goods and services. The labour component includes both the unemployment rate and live register figures. It should be noted that both labour market measures include those who were in receipt of pandemic income supports and therefore represent the COVID-19 adjusted or upper-bound measures of the labour market[3]. Fiscal indicators are comprised of tax revenues as provided by the Department of Finance and include VAT and income tax receipts. Output is comprised of sub sectors of the industrial production and turnover index (IPT) which is collected monthly from a sample of 1,081 enterprises. As pointed out by Conefrey and Walsh (2018), although overall industrial production is a highly relevant indicator of economic activity for most countries, in the Irish case it includes the impact of

[2] All monthly indicators are available from at least 2003M1, with the exception of the Housing and Retail Sales variables which are both available from 2005M1. The raw data is transformed as follows:
1. Annual Change = All Housing, Fiscal Labour indicators and Car Registration data.
2. Annual % Change = All Output, Retail Sales and Price indicators.
3. Log Difference = Exchange Rates and ISEQ All Share Index.
4. No Change = All Soft/Survey indicators and Interest Rates.

[3] See the CSO for details on Ireland's labour market statitcs during the COVID-19 pandemic, https://www.cso.ie/en/releasesandpublications/in/mue/inlrmue/

goods produced abroad under contract manufacturing arrangements. Therefore, the focus is on industrial production in the traditional sector in an attempt to better capture output produced by domestic firms. We also omit those sub-sectors which have a large multi national enterprise (MNE) presence such as pharmaceutical and those related to information and communications technology (ICT). Finally, for soft or survey indicators, the data used is sourced from the European Commission's (EC) Business and Consumer Surveys. These harmonised surveys are conducted by the Directorate General for Economic and Financial Affairs of the EC and are addressed to representatives of the industry, manufacturing, services, retail trade and construction sectors, as well as to consumers across the EU.

As the variables are released in a staggered manner[4], any estimations can be updated regularly as new data and new information is provided. This presents a potential 'jagged' edge problem i.e. unbalanced data sets with missing values at the end of the sample period which occurs when data become available with different delays. However, the methodology used in the estimation process, outlined in Section 3, can circumnavigate this issue.

3 METHODOLOGY

The methodological approach used in this paper can be divided into two sections. Firstly, it applies a dynamic factor model (DFM) to the panel of monthly indicators in order to extract a single measure of Irish economic activity. Secondly, it links this single measure to MDD using two standard techniques in the nowcasting literature - bridge equations and mixed data sampling (MIDAS).

3.1 Dynamic Factor Model (DFM)

DFMs are parsimonious representations of relationships among time series variables. The premise of a DFM is that a few latent dynamic factors drive the co-movements of a high-dimensional vector of time-series variables which are also affected by a idiosyncratic disturbances (Stock & Watson, 2016). With the surge in data availability over the last number of years, DFMs have proven to be indispensable in macroeconomic forecasting (Doz & Fuleky, 2020). The parameters of DFMs can be estimated by the method of principal component analysis (PCA). This method is easy to compute, and is consistent under quite general assumptions as long as both the cross-section and time dimension grow large. It suffers, however, from a large drawback: the data set must be balanced such that the start and end points of the sample are the same across all observable time series (Solberger & Spånberg, 2020). Therefore, Giannone et al. (2008) advocate a two-step estimation of the factors in a dynamic approximate factor model when the panel of time series is large. In

[4] Details on the schedule of Irish monthly indicator release is provided by Daly and Rehill (2020)

the first step, the parameters of the model are estimated from an OLS on principal components. In the second step, the factors are estimated via the Kalman smoother. The Kalman technique provides a convenient and natural framework for handling the irregularities of data in real time such as mixed frequencies and non synchronicity of the data releases (Bok et al., 2017), and thus overcomes the unbalanced dataset drawback of the PCA technique.

The DFM can be expressed as in Stock and Watson (2016) as Equations 1 and 2 below. Equation 1, the signal equation, links the observed series to the unobserved factors while Equation 2, the state equation, describes the evolution of the factors over time. Equation 1 expresses an N x 1 vector X_t of observed time series variables (which are the monthly indictors as described in Section 2) as depending on a smaller number, R, of unobserved latent factors f_t and an idiosyncratic component[5]. The variables X_t are loaded[6] into the unobserved factors f_t through Λ. Equation 2 describes the latent factors f_t as following a time series process which is commonly taken to be a vector autoregression (VAR)

$$X_t = \Lambda(L) f_t + \varepsilon_t \tag{1}$$

$$f_t = \Psi(L) f_{t-1} + \eta_t \tag{2}$$

Where ε_t is the idiosyncratic componet and (L) is the lag operator. The lag polynomial matrices $\Lambda(L)$ and $\Psi(L)$ are N x q and q x q respectively. η_t is a R x 1 vector of serial uncorrelated innovations to the factors, f_t. The i^{th} row of $\Lambda(L)$, the lag polynomial $\Lambda_i(L)$, is called the dynamic factor loading for the i^{th} series, X_{it} while $\Lambda_i(L) f_t$ is called the common component of the i^{th} series. The number of factors R is generally unknown and therefore needs to be either estimated or assumed. Popular estimators for the number of factors in approximate factor models can be found in Bai and Ng (2002), Onatski (2010) and Ahn and Horenstein (2013). However, as pointed out by Solberger and Spånberg (2020), for the purposes of nowcasting the appropriate number of factors is more of a practical concern and can be found from forecasting evaluations. The preliminary estimations for this paper found that a single factor provides the best explanation for movements in Irish economic activity.

3.2 Bridge-Equations and Mixed Data Sampling (MIDAS)

Once estimated, the single factor, which is represented by a monthly time series, can be applied to nowcast the macroeconomic variable in question – in this case MDD. In this paper, we test the nowcasting performance of two single-equation approaches from the wider

[5] Estimation of dynamic factor models concern foremost the common component; the idiosyncratic component is generally considered residual (Solberger & Spånberg, 2020).

[6] The relationship of each monthly indicator to the underlying latent factor is expressed by the so-called factor loading.

nowcasting literature - bridge equations and mixed-data sampling (MIDAS). Bridge equations have a long tradition in short-term forecasting, and are often used by central banks and policy-making institutions (see Baffigi, Golinelli, and Parigi (2004) and Parigi and Golinelli (2007) among many others). In particular, bridge models have been the workhorse for nowcasting, typically being used to explain GDP growth by time aggregated indicators of economic activity such as business cycle indicators (Schumacher, 2016). This technique involves forecasting high-frequency indicators with auxiliary models, and using the results to forecast a low-frequency target variable. A nowcast of the quarterly macroeconomic variable can therefore be estimated by regressing MMD_t on the estimated indicator of economic activity which been transformed from a monthly to a quarterly series. The bridge equation can be written as:

$$MDD_t = \alpha + \sum_{j=1}^{R} \beta_j f_{j,t}^{Q} \tag{3}$$

Where α and β_j are estimated regression parameters, and $f_{j,t}^{Q}$ are quarterly averages of the monthly factors $f_{j,t}$. Equation 3 is resolved through two stages as follows: (1) the monthly factor is projected for the current period through the DFM and then aggregated to obtain a quarterly value, $f_{j,t}^{Q}$; (2) this aggregated factor value is then set as the regressor against the target variable, MDD_t . Equation 3 above represents the simplest version of the bridge equation used in this paper and a number of different specifications are tested, details of which can be found later in the paper Table 2.

In the more recent academic literature, another single-equation approach for nowcasting called mixed-data sampling, or MIDAS has emerged. Originally proposed by Clements and Galvão (2008) and Ghysels, Sinko, and Valkanov (2007), this technique was motivated by the perceived flaw of the aggregation process involved in the bridge equation approach which has the potential to lose some of the important information from the data. MIDAS can be described as a 'direct' nowcasting technique in that the dependent variable representing lower-frequency, quarterly data (MDD_t) is regressed against a distributed lag of the independent variable, representing higher-frequency, monthly data. The basic MIDAS representing can be written as:

$$MDD_t = \alpha + \sum_{j=1}^{R} \beta_j f_{j,t}^{M} \tag{4}$$

Where $f_{j,t}^{M}$ are the monthly factors, or single factor as in this papers case represented by the estimated monthly indicator. Usually models of the MIDAS-class use lag polynomials of a specific function, which impose some structure on the weights of regressors included in the model (Barsoum & Stankiewicz, 2015). However, Foroni, Marcellino, and Schumacher (2015) show by means of Monte Carlo simulations that for small differences in frequencies of the analysed variables, MIDAS with unrestricted lag polynomial (U-MIDAS), that is a model for which the estimated regressor weights are not restricted by any function, perform better than restricted MIDAS. As for most macroeconomic applications, this paper is dealing with quarterly and monthly data and thus the difference in frequencies of the variables is small suggesting that the U-MIDAS approach may be the most appropriate. The performance of both the restricted and unrestricted are tested in Table 2.

4 RESULTS

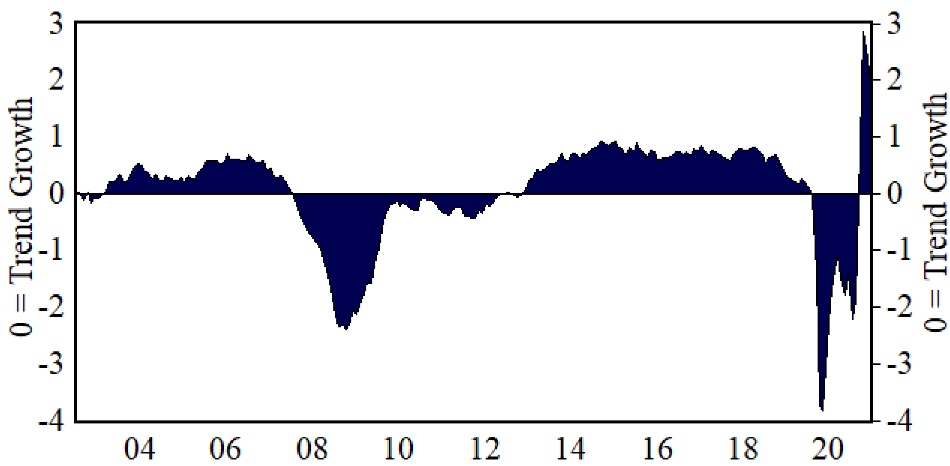
The results of this paper can be divided into two subsections. Firstly, Section 4.1 will examine the ability of the economic indicator (as estimated through Equations 1 and 2) to map the dynamics of Irish domestic economic activity. As part of this analysis, the paper will also examine the decomposition of changes in the indicator over two key time periods by focusing on the dynamics in the aftermath of the 2007-2008 Global Financial Crisis (GFC) and the 2020-21 COVID-19 pandemic. Secondly, Section 4.2 will examine if the indicator can be used to accurately nowcast MDD.

4.1 An Estimated Monthly Economic Activity Indicator for Ireland

As discussed in Section 3, the DFM estimated in this paper can extract a single factor which summarises the movement and variation of a large number of variables related to economic activity. Figure 1 illustrates the single factor, f_t as estimated by the DFM, which can be referred to as a monthly indicator of Irish economic activity. Similar to the Central Bank of Ireland's BCI, the indicator provides a qualitative measure of the economic cycle, with a value above and below 0 representing above and below average trend growth respectively. From a simple visual observation, it would appear that the monthly series captures movements in the level of Irish economic activity quite well over the last twenty or so years. For example, we see the large fall and sluggish recovery in the aftermath of the GFC in 2007-08 as well as the staggered fall and recovery in economic activity resulting from various tightening and easing of public health restrictions during the COVID-19 pandemic in 2020-21.

By converting the monthly dataset into a quarterly series we can also compare it against two key macroeconomic indicators - MDD and GDP. Table 1 looks at a simple correlation (ρ) between the indicator and these two key variables, both over the entire period of data availability and across rolling windows of 10 years (40 quarters). The indicator has a strong relationship with MDD over the entire estimation period and has remained relatively

Figure 1: Indicator of Irish Economic Activity ((2003M1 - 2021M6)



constant across the rolling windows. The relationship with the estimated indicator and GDP on the other hand has seen a rapid deterioration, particularly post 2011. This result is not surprising given issues with relating GDP figures to the level of domestic economic activity as discussed in Section 1.

An interesting extension to the analysis is to examine the role that the various components or blocks, as described in Section 2, have played in the indicators dynamics over two of the more volatile periods across the estimation period. Therefore, by using the loading factors produced by the DFM, a comparison of the periods just before and after the 2007-2008 GFC and the 2020-21 COVID-19 pandemic is undertaken. By examining the historical composition of both of these periods, the key drivers of contraction and/or recovery in activity can be identified. The decomposition across both periods can be seen in Figure 2. One noticeable difference between the composition across the two crises is the contribution of housing (dark red) to the decline during the April 2008 to December 2009 period. Contrary to this, the decomposition during the recent COVID-19 period shows that housing actually contributed to the recovery in activity seen in April and May 2021, although its contribution was negligible compared to that of consumption, labour and survey indicators. Another noticeable difference is the contribution of changes to the price level (dark grey) across both periods. Figure 2 shows that the deflationary effect of the GFC contributed consistently to the decline in the indicator from January 2009 onward. The same cannot be said for the COVID-19 period however, as there is no evidence of consumer prices contributing to the indicator in the way one would expect during a period of economic contraction. In fact, there has been much discussion regarding the increases

Table 1: Correlation (ρ) between Indicator and MDD &GDP

Period		MDD	GDP
Full	2003Q1 - 2020Q4	**0.87**	**0.53**
Sample 1	2004Q1 - 2012Q3	*0.86*	*0.89*
Sample 2	2013Q1 - 2020Q4	*0.93*	*0.27*
10 Year (40 Quarter) Rolling Window	2004Q1 - 2013Q4	*0.86*	*0.87*
	2005Q1 - 2014Q4	*0.86*	*0.88*
	2006Q1 - 2015Q4	*0.89*	*0.74*
	2007Q1 - 2016Q4	*0.89*	*0.69*
	2008Q1 - 2017Q4	*0.90*	*0.70*
	2009Q1 - 2018Q4	*0.92*	*0.67*
	2010Q1 - 2019Q4	*0.86*	*0.65*
	2011Q1 - 2020Q4	*0.89*	*0.33*

in consumer prices in 2021 due to a number of factors including increases in input costs related to supply disruptions and one-off re-opening effects on services prices.[7]

4.2 Nowcasting Modified Domestic Demand (MDD)

In this section, the paper takes the estimated monthly indicator and applies the bridge equation and MIDAS techniques outlined in Section 3 in order to investigate the ability of the indicator to provide real time estimates of MDD. This is done by performing 1-step ahead forecasts [8] A number of different specifications across the two techniques are applied. For the bridge equation, both a static and dynamic equation were estimated. Due to the evidence of structural breaks, as detected by a Bai and Perron (2003) multiple breakpoint test[9], a bridge equation using a least squares regression with breakpoints was also estimated[10]. For the MIDAS technique, both a restricted and unrestricted version were estimated. The performance of all bridge equation and MIDAS nowcasts were tested using a number of different forecast performance measures which are standard in the literature.

[7] See remarks of Governor of Central Bank of Ireland on ”Slack, bottlenecks, and post-pandemic inflation” `https://www.centralbank.ie/news/article/speech-gabriel-makhlouf-dublin-economics-workshop-slack-bottlenecks-and-post-pandemic-inflation-17-september-2021`

[8] As pointed out by , the 1-step ahead forecasts are equivalent to nowcast estimates as in practice, these models would only be used for their 1-step ahead prediction

[9] Bai-Perron tests of L+1 vs. L sequentially determined breaks indicates two break dates at 2009Q3 and 2012Q1

[10] Following the initial work of Stock and Watson (1996) papers such as Inoue and Rossi (2011) show the importance of identifying parameter instabilities for improving the forecasting performance

Figure 2: Decomposition of Changes to the Monthly Indicator of Economic Activity (GFC vs. COVID-19)

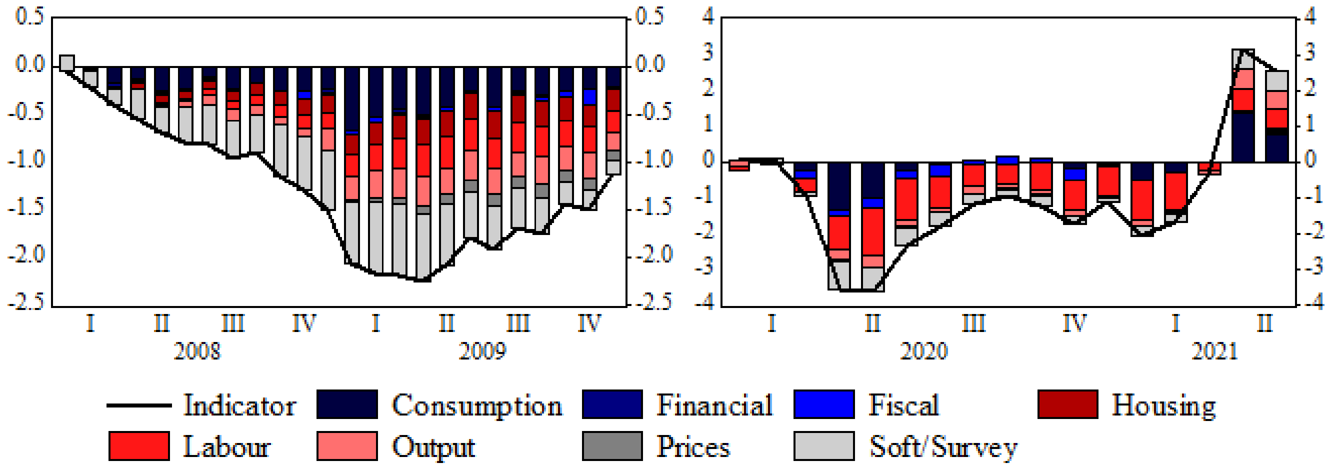
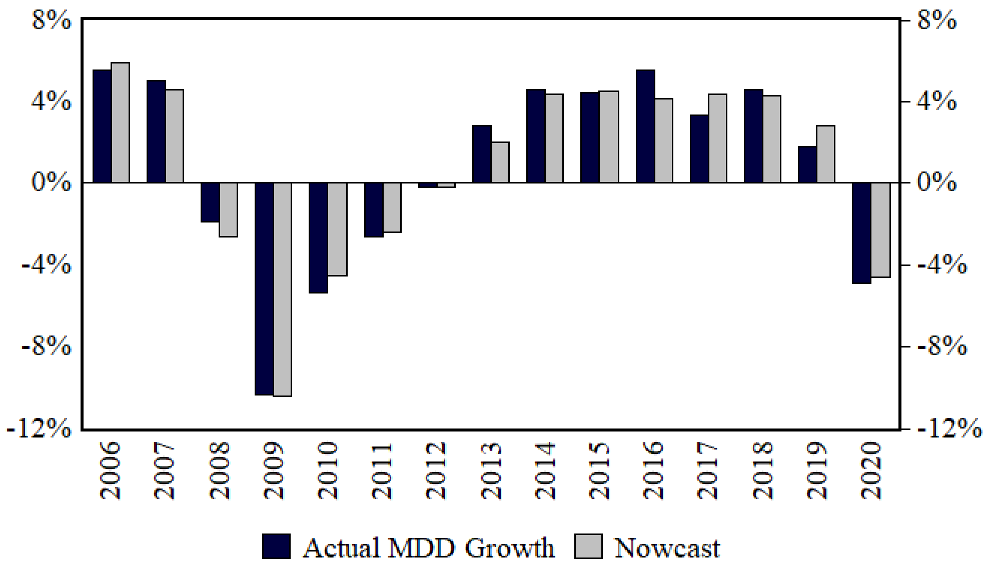


Table 2: Model Performance Analysis of Nowcasting MDD (2006Q1 2020Q4)

Model Type	Model Description	RMSE	MAE	Theil U1	MAPE
Bridge Equation	Static	2.42	1.86	0.24	74.12
	Dynamic	1.73	1.42	0.17	58.49
	Breakpoint	1.21	0.96	0.12	43.06
MIDAS	Restricted	2.36	1.83	0.23	75.49
	Unrestricted	2.35	1.82	0.23	74.79

This includes RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error) and the Theil Inequality Coefficient. The illustration of all nowcast series as well as their forecast evaluations can be seen in Figure 5 (Appendix II) and Table 2 respectively. Although Figure 5 indicates that all estimated series follow the general path of MDD, the test statistics in Table 2 clearly show that the bridge equation which accounts for structural breaks outperforms all other estimations. Figure 3 evaluates the in-sample forecasts of MDD using this best performing model by converting the quarterly nowcast values into annual data. The figure shows that the nowcast model has tracked the growth rate fairly well over the last fifteen years or so with a relatively close fit between the actual MDD growth rate and the fitted values from the nowcast model. This includes the period during the GFC with the nowcast producing MDD growth rates of 4.6%, -2.6%, -10.4% and -4.5% for 2007, 2008, 2009 and 2010 respectively versus the actual values of 5.0%, -1.9%, -10.4% and -5.3%. Figure 4 also shows that the nowcast continued to provide a relatively close fit over the more volatile COVID-19 period, despite the unprecedented nature of the shock to the level of economic activity

Figure 3: Actual MDD Growth Rate vs Nowcast (2006-2020)



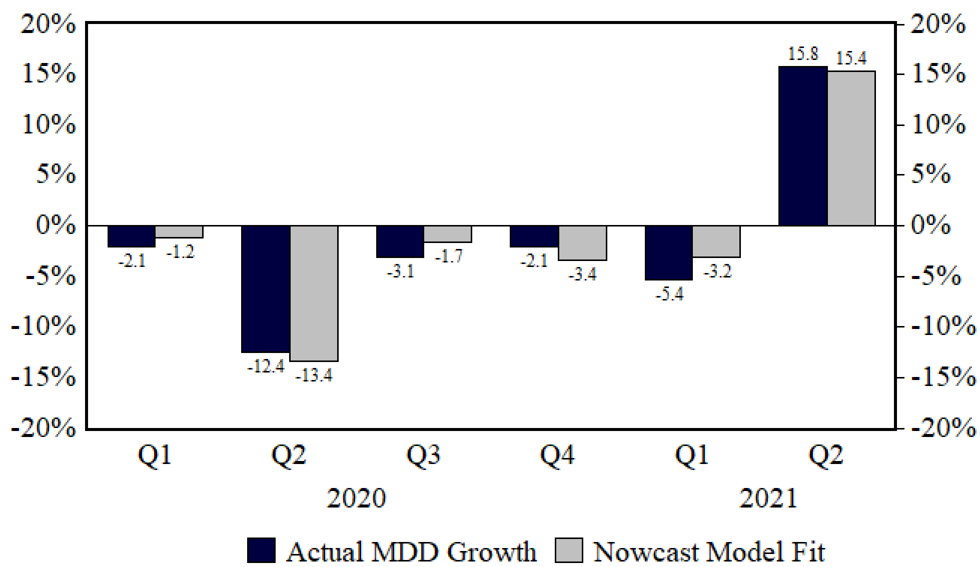
5 Conclusion

The main aim of this paper is to provide a framework for tracking the Irish domestic economy in real time using high frequency indicators. It applies a dynamic factor model to a panel of monthly variables which in turn produces a single measure indicative of the dynamics of Irish economic activity. It then applies a bridge equation to produce a nowcast of MDD. Both the monthly indicator of economic activity and the nowcast can be 'refreshed' frequently as new data is released. One of the key benefits of this is that the model can update incrementally in real-time in response to new incoming data from the monthly indicators thus lowering the likelihood of forecasts becoming out-dated.

The results in the paper show that the estimated indicator of economic activity has a strong relationship with MDD over the entire sample period of 2003-2020. The same cannot be said for GDP however, with a strong deterioration in the relationship since 2011. This is likely due to the well documented issues with Ireland's national accounts. The paper also finds that the estimated indicator of economic activity can be used to accurately produce a nowcast of MDD growth. In addition, a series of forecast evaluation tests finds that a bridge equation which accounts for structural breaks provides the best performing nowcast of MDD.

Both the monthly indicator of economic activity and the nowcast of MDD as described in this paper can be used to monitor economic developments in real time. These tools can assist policymakers overcome the difficulties related to decision making that comes from the delay in publication of key variables like economic growth. This is particularly useful during times of crisis or economic distress, such as during the COVID-19 pandemic, when access to timely information is crucial to facilitate the appropriate data-driven policy response.

Figure 4: Actual MDD Growth Rate vs Nowcast During COVID-19 (2020Q1-2021Q2)



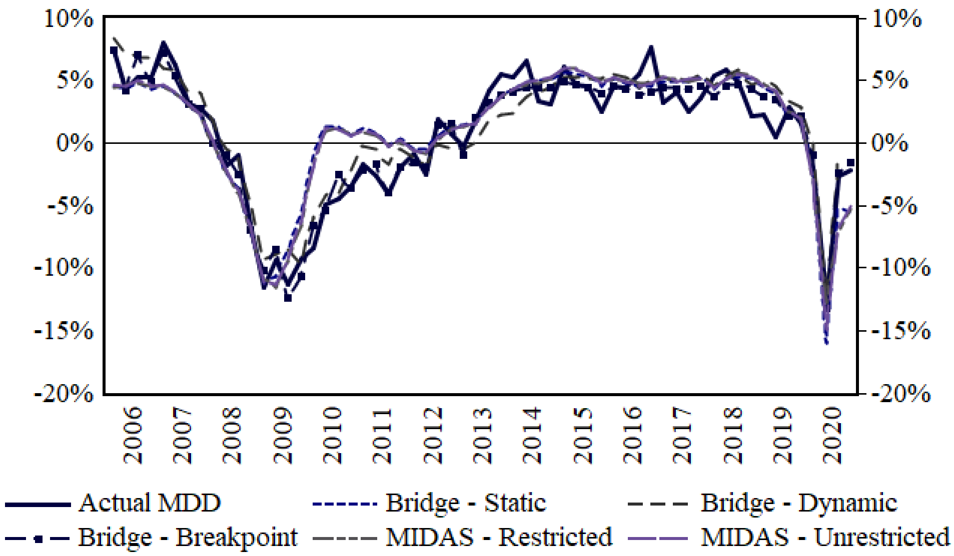
APPENDIX I

Table 3: List of Monthtly Indictators

	Variable	Source (Reference/Code)
Output	Industrial Production, Traditional sector˜	CSO (MIM03)
	Industrial Production, Food products	CSO (MIM03)
	Industrial Production, Paper and paper products	CSO (MIM03)
	Industrial Production, Transport equipment˜	CSO (MIM03)
	Industrial Production, Other foods˜	CSO (MIM03)
	Industrial Production, Grain mill and starch products	CSO (MIM03)
	Industrial Production, Meat and meat products	CSO (MIM03)
	Industrial Production, Dairy products˜	CSO (MIM03)
	Industrial Production, Bakery and farinaceous products	CSO (MIM03)
	Industrial Production, Wood and wood products, except furniture	CSO (MIM03)
	Industrial Production, Rubber and plastic products	CSO (MIM03)
	Industrial Production, Other non-metallic mineral products˜	CSO (MIM03)
Soft/Survey	European Commission (EC) Service Sector Survey - Ireland	EC (IE.SERV)
	European Commission (EC) Consumer Survey - Ireland	EC (IE.CONS)
	European Commission (EC) Retail Sector Survey - Ireland	EC (IE.RETA)
	European Commission (EC) Construction Sector Survey - Ireland	EC (IE.BUILD)
	European Commission (EC) Industy/Business Climate Indicator - Ireland	EC (IE.INDU)
	European Commission (EC) Economic Sentiment Indicator - Ireland	EC (IE.EEI)
	European Commission (EC) Employment Expectations Indicator- Ireland	EC (IE.ESI)
	European Commission (EC) Economic Sentiment Indicator - EU	EC (EU.ESI)
	European Commission (EC) Economic Sentiment Indicator - Eurozone	EC (EA.ESI)
Labour	Persons on the Live Register (SA) All Ages, Both Sexes	CSO (LRM02)
	Persons on the Live Register (SA) All Ages, Male	CSO (LRM02)
	Persons on the Live Register (SA) All Ages, Female	CSO (LRM02)
	Seasonally Adjusted Monthly Unemployment Rate, Both Sexes	CSO (MUM01)
	Seasonally Adjusted Monthly Unemployment Rate, Male	CSO (MUM01)
	Seasonally Adjusted Monthly Unemployment Rate, Female	CSO (MUM01)
Consumption	Vehicles Licensed, All Vehicles	CSO (TEM01)
	Vehicles Licensed, New Vehicles	CSO (TEM01)
	Retail Sales: All retail businesses, excluding motor trades	CSO (RSM05)
	Retail Sales: Department stores	CSO (RSM05)
	Retail Sales: Pharmaceutical, medical and cosmetic articles˜	CSO (RSM05)
	Retail Sales: Hardware, paints and glass˜	CSO (RSM05)
	Retail Sales: Electrical goods˜	CSO (RSM05)
	Retail Sales: Books, newspapers and stationery˜	CSO (RSM05)
Fiscal	Tax Revenue, Total	Department of Finance (DATABANK)
	Tax Revenue, Stamps	Department of Finance (DATABANK)
	Tax Revenue, Income Tax	Department of Finance (DATABANK)
	Tax Revenue, Valued Added Tax	Department of Finance (DATABANK)
Financial	Exchange Rate: US Dollar per Euro	ECB SDW (EXR.M.USD.EUR)
	Exchange Rate: Pound Sterling per Euro	ECB SDW (EXR.M.GBP.EUR)
	Interest Rate: Interbank market rate 3 months fixed	ECB SDW (EURIBOR3MD_HSTA)
	Interest Rate: ECB - marginal lending rate	ECB SDW (EUR.4F.KR.DFR.LEV)
	Interets Rate: Government 10 year bond yield	ECB SDW (IE.L.L40.CI.0000.EUR.N.Z)
	ISEQ All Share Index	Euronext (IE0001477250)
Housing	Residential Property Price Index: National - all residential properties	CSO (HPM06)
	Residential Property Price Index: National - houses	CSO (HPM06)
	Residential Property Price Index: National - apartments	CSO (HPM06)
Prices	Consumer Price Index: All Items	CSO (CPM01)
	Consumer Price Index: Goods	CSO (CPM02)
	Consumer Price Index: Services	CSO (CPM03)

APPENDIX II

Figure 5: Actual MDD vs All Nowcast Models (2006Q1-2020Q4)



References

Aastveit, K., & Trovik, T. (2012). Nowcasting Norwegian GDP: The Role of Asset Prices in a Small Open Economy. *Empirical Economics*, *42*(1), 95-119.

Ahn, S. C., & Horenstein, A. R. (2013). Eigenvalue Ratio Test for the Number of Factors. *Econometrica*, *81*(3), 1203–1227. Retrieved from http://www.jstor.org/stable/23524174

Angelini, E., Camba-Mendez, G., Giannone, D., Reichlin, L., & Rünstler, G. (2011). Short-term Forecasts of Euro Area GDP Growth. *The Econometrics Journal*, *14*(1), C25–C44. Retrieved from http://www.jstor.org/stable/23127215

Baffigi, A., Golinelli, R., & Parigi, G. (2004). Bridge Models to Forecast the Euro Area GDP. *International Journal of Forecasting*, *20*(3), 447-460. Retrieved from https://EconPapers.repec.org/RePEc:eee:intfor:v:20:y:2004:i:3:p:447-460

Bai, J., & Ng, S. (2002). Determining the Number of Factors in Approximate Factor Models. *Econometrica*, *70*(1), 191-221. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/1468-0262.00273 doi: https://doi.org/10.1111/1468-0262.00273

Bai, J., & Perron, P. (2003). Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics*, *18*(1), 1-22. Retrieved from https://EconPapers.repec.org/RePEc:jae:japmet:v:18:y:2003:i:1:p:1-22

Barsoum, F., & Stankiewicz, S. (2015). Forecasting GDP Growth Using Mixed-Frequency Models with Switching Regimes. *International Journal of Forecasting*, *31*(1), 33-50. Retrieved from https://EconPapers.repec.org/RePEc:eee:intfor:v:31:y:2015:i:1:p:33-50

Bańbura, M., Giannone, D., Modugno, M., & Reichlin, L. (2013). Chapter 4 - Nowcasting and the Real-Time Data Flow. In G. Elliott & A. Timmermann (Eds.), *Handbook of economic forecasting* (Vol. 2, p. 195-237). Elsevier. Retrieved from https://www.sciencedirect.com/science/article/pii/B9780444536839000049 doi: https://doi.org/10.1016/B978-0-444-53683-9.00004-9

Bańbura, M., & Rünstler, G. (2011). A Look into the Factor Model Black Box: Publication Lags and the Role of Hard and Soft Data in Forecasting GDP. *International Journal of Forecasting*, *27*(2), 333-346. Retrieved from https://www.sciencedirect.com/science/article/pii/S0169207010000191 doi: https://doi.org/10.1016/j.ijforecast.2010.01.011

Bermingham, C. (2006). *An Examination of Data Revisions in the Quarterly National Accounts* (Research Technical Papers No. 10/RT/06). Central Bank of Ireland. Retrieved from https://ideas.repec.org/p/cbi/wpaper/10-rt-06.html

Bok, B., Caratelli, D., Giannone, D., Sbordone, A. M., & Tambalotti, A. (2017). *Macroeconomic Nowcasting and Forecasting with Big Data* (Staff Reports No. 830). Federal Reserve Bank of New York. Retrieved from https://ideas.repec.org/p/fip/fednsr/830.html

Byrne, D., Morley, C., & McQuinn, K. (2014). *Nowcasting and the Need for Timely Estimates of Movements in Irish Output* (Research Notes No. RN2014/3/1). Economic and Social Research Institute (ESRI). Retrieved from https://ideas.repec.org/p/esr/resnot/rn2014-3-1.html

Clements, M. P., & Galvão, A. B. (2008). Macroeconomic Forecasting with Mixed-Frequency Data: Forecasting Output Growth in the United States. *Journal of Business Economic Statistics*, *26*(4), 546–554. Retrieved from http://www.jstor.org/stable/27639011

Conefrey, T., & Walsh, G. (2018). *A Monthly Indicator of Economic Activity for Ireland* (Economic Letters No. 14/EL/18). Central Bank of Ireland. Retrieved from https://ideas.repec.org/p/cbi/ecolet/14-el-18.html

D'Agostino, A., McQuinn, K., & O'Brien, D. (2008). *Nowcasting Irish GDP* (Research Technical Papers No. 9/RT/08). Central Bank of Ireland. Retrieved from https://ideas.repec.org/p/cbi/wpaper/9-rt-08.html

Daly, L., & Rehill, L. (2020). *Where Are We Now? Examining Irish Economic Developments in Real-Time* (Research Paper No. 04/20). Department of Finance. Retrieved from https://www.gov.ie/en/publication/e6b3a7-where-are-we-now-examining-irish-economic-developments-in-real-time/

Doz, C., & Fuleky, P. (2020). *Dynamic Factor Models - Macroeconomic Forecasting in the Era of Big Data, 2020*. Volume 52.

Fitzgerald, J. (2018). *National Accounts for a Global Economy: the Case of Ireland* (Trinity Economics Papers No. tep0418). Trinity College Dublin, Department of Economics. Retrieved from https://ideas.repec.org/p/tcd/tcduee/tep0418.html

Foroni, C., Marcellino, M., & Schumacher, C. (2015). Unrestricted Mixed Data Sampling (MIDAS): MIDAS Regressions with Unrestricted Lag Polynomials. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, *178*(1), 57–82. Retrieved from http://www.jstor.org/stable/43965717

Ghysels, E., Sinko, A., & Valkanov, R. (2007). MIDAS Regressions: Further Results and New Directions. *Econometric Reviews*, *26*(1), 53-90. Retrieved from https://EconPapers.repec.org/RePEc:taf:emetrv:v:26:y:2007:i:1:p:53-90

Giannone, D., Reichlin, L., & Small, D. (2008). Nowcasting: The Real-Time Informational Content of Macroeconomic Data. *Journal of Monetary Economics*, *55*(4), 665-676. Retrieved from https://ideas.repec.org/a/eee/moneco/v55y2008i4p665-676.html

Higgins, P. (2014). GDPNow: A Model for GDP 'Nowcasting'. *FRB Atlanta Working Paper 2014-7*. doi: http://dx.doi.org/10.2139/ssrn.2580350

Huber, F., Koop, G., Onorante, L., Pfarrhofer, M., & Schreiner, J. (2020). Nowcasting in a Pandemic Using Non-Parametric Mixed Frequency VARs. *Journal of Econometrics*. Retrieved from https://www.sciencedirect.com/science/article/pii/S0304407620303936 doi: https://doi.org/10.1016/j.jeconom.2020.11.006

Inoue, A., & Rossi, B. (2011). Identifying the Sources of Instabilities in Macroeconomic Fluctuations. *The Review of Economics and Statistics*, *93*(4), 1186-1204. Retrieved from https://ideas.repec.org/a/tpr/restat/v93y2011i4p1186-1204.html

Liebermann, J. (2011). *Real-Time Nowcasting of GDP: Factor Model versus Professional Forecasters* (Research Technical Papers No. 3/RT/11). Central Bank of Ireland. Retrieved from https://ideas.repec.org/p/cbi/wpaper/3-rt-11.html

Marcellino, M., & Sivec, V. (2021). Nowcasting GDP Growth in a Small Open Economy. *National Institute Economic Review*, *256*, 127–161. doi: 10.1017/nie.2021.13

Onatski, A. (2010). Determining the Number of Factors from Empirical Distribution of Eigenvalues. *The Review of Economics and Statistics*, *92*(4), 1004–1016. Retrieved from http://www.jstor.org/stable/40985808

Parigi, G., & Golinelli, R. (2007). The Use of Monthly Indicators to Forecast Quarterly GDP in the Short Run: An Application to the G7 Countries. *Journal of Forecasting*, *26*(2), 77-94. Retrieved from https://EconPapers.repec.org/RePEc:jof:jforec:v:26:y:2007:i:2:p:77-94

Richardson, A., van Florenstein Mulder, T., & Vehbi, T. (2021). Nowcasting GDP Using Machine-Learning Algorithms: A Real-Time Assessment. *International Journal of Forecasting*, *37*(2), 941-948. Retrieved from https://www.sciencedirect.com/science/article/pii/S016920702030159X doi: https://doi.org/10.1016/j.ijforecast.2020.10.005

Schumacher, C. (2016). A Comparison of MIDAS and Bridge Equations. *International Journal of Forecasting*, *32*(2), 257-270. Retrieved from https://www.sciencedirect.com/science/article/pii/S0169207015001144 doi: https://doi.org/10.1016/j.ijforecast.2015.07.004

Solberger, M., & Spånberg, E. (2020). Estimating a Dynamic Factor Model in EViews Using the Kalman Filter and Smoother. *Computational Economics*, *55*(3), 875-900. Retrieved from https://ideas.repec.org/a/kap/compec/v55y2020i3d10.1007_s10614-019-09912-z.html doi: 10.1007/s10614-019-09912-

Stock, J., & Watson, M. (1996). Evidence on Structural Instability in Macroeconomic Time Series Relations. *Journal of Business Economic Statistics*, *14*(1), 11-30. Retrieved from https://EconPapers.repec.org/RePEc:bes:jnlbes:v:14:y:1996:i:1:p:11-30

Stock, J., & Watson, M. (2016). Chapter 8 - Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics. In J. B. Taylor & H. Uhlig (Eds.), (Vol. 2, p. 415-525). Elsevier. Retrieved from https://www.sciencedirect.com/science/article/pii/S1574004816300027 doi: https://doi.org/10.1016/bs.hesmac.2016.04.002