Nowcasting Mexican GDP Based On Electricity Consumption[1]

Final Project Report

Executive Summary

The Mexican Government's ability to formulate and assess policies is constrained by a lack of frequent/timely estimates of economic activity at the national, state and municipality-level. In collaboration with the Office of the President of Mexico, this project seeks to address the problem by leveraging a set of national/state-level data over the period 2009 to 2014 to develop a national/state-level quarterly GDP nowcasting model which is also applicable to the municipality-level.

Electricity consumption-based nowcasting, based on a theoretically founded link between electricity consumption and GDP, promises to provide the government with near real-time estimates of quarterly GDP given that electricity consumption data is available at a monthly frequency at the national, state and municipality-level with only a minimal publication lag. The project's emphasis is on providing a 'Proof of Concept', i.e. an illustration that electricity-based nowcasting is feasible and informative. To substantiate the analysis the potential of electricity-based nowcasting models to produce short-term forecast of quarterly GDP at the end of a quarters 1st/2nd month and the potential additional gains associated with expanding the covariate set beyond electricity-related information are also explored.

Electricity-based nowcasting models are estimated using OLS techniques appropriate for a panel composed of Mexico's 32 states and assessed on the basis of their out-of-sample performance, i.e. their nowcasts over an 8-quarter testing set. To explore the gains associated with incorporating electricity based information into the GDP nowcasting process models are evaluated on the basis of the out-of sample RMSE relative to that of an atheoretical autoregressive (AR) model.

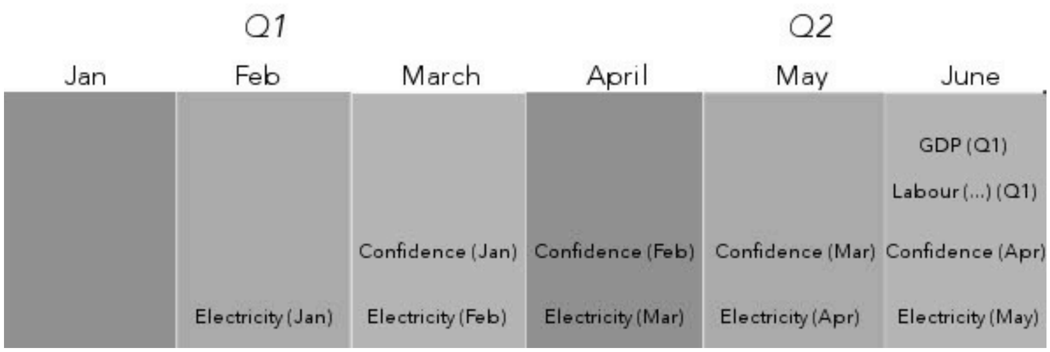
The results attest to the importance of accounting for the evolution of the electricity-GDP relation across time and states and reveal the effect of economic stability and state-level economic structures upon the relative informativeness of an electricity consumption based model and an AR model. A model averaging-based nowcasting model incorporating both of these findings outperforms the AR model at the state and national level – a promising and economically significant result: The model averaging based-nowcast correctly nowcasts the sign of state's GDP growth 92.3% of the time compared to 80.6% for the AR model. A forecast produced at the end of the 1st month is still accurate 84% of the time. Integrating forward looking and easily collectable survey data into the model averaging-based approach is likely to further improve model performance.

Project Report

Part I - Project Overview

The Mexican Government is compelled to formulate and assess policies on the basis of infrequent and out-of date estimates of economic activity: Preliminary GDP estimates at the national and state-level are available at a quarterly frequency but published with a 1 quarter lag (see *Figure-1*) while estimates of GDP at the municipality-level are available once every 5 years. Estimates of other economic indicators which could serve as GDP proxies, including unemployment, wages, inflation and industrial output, are released similarly infrequently.

Figure-1: Mexican National and State-Level Data Release Schedule (Q1 - Q2: Q1, Q2 data)



Labor (…) refers to a range of economic indicators including unemployment, wages, inflation and industrial output
Variables followed in brackets by the period the data refers to

Against this background, the Government's objective is to obtain timely quarterly estimates of Mexican GDP at the national, state and municipality-level. A 'Proof of Concept' in particular - an illustration that the generation of *informative* quarterly GDP estimates *is* feasible given the Government's statistical capacities – is expected to serve as an impetus for the further strengthening of the statistical capacities necessary to produce real-time estimates of economic activity.

On the basis of the available data – taking into account the unavailability of municipality-level and sectorally disaggregated data[2] – this project seeks to provide such a 'Proof of Concept' by:

- ➢ Developing and evaluating the performance of nowcasting[3] models producing quarterly *state and national-level* GDP estimates
- ➢ Assessing the broader potential of the proposed approach by (i) assessing the

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[2] In light of unforeseen events, including Hurricane Odile, affecting the Mexican Government (i) GDP/electricity related data did not became available in a sectorally disaggregated format and (ii) while electricity consumption became available at the municipality-level, GDP became available only at the state/national-level

[3] "The prediction of the present, very near future and very recent past using information available more timely and frequently than the target variable of interest" (BOE, 2014)

performance of short-term forecasts of quarterly *state/national-level* GDP released at the end of the 1st/2nd month of a quarter and (ii) evaluating the effect upon model performance of augmenting the covariate set

- Providing a discussion of how the models *could* be applied by the Government to the *municipality-level* once the required data becomes available

Part II of the report introduces electricity based-nowcasting as a promising approach. Part III discusses the methodology. The findings are discussed in Part IV and framed in terms of their policy relevance and implications in Part V.

Part II - Electricity-Based Nowcasting

Single indicator electricity consumption-based nowcasting, i.e. nowcasting based only on electricity consumption-related information, presents a methodology with the potential to address the requirements of the Mexican Government.

Numerous nowcasting studies have incorporated electricity consumption data – examples which highlight the broad applicability and promise of such an approach include the Bank of England's (BOE) (2014) exploration of sectorally disaggregated composite indicator nowcasting models applied to UK quarterly GDP; Mancellari's (2010) combination of economic indicators and survey data to nowcast quarterly GDP in Albania; and Bhattacharya et al.'s (2011) nowcasting of quarterly Indian GDP using a limited number of hard economic indicators.

Single indicator electricity consumption based-nowcasting is both theoretically founded and practically feasible within a Mexican context:

- *On a theoretical level*, a link between electricity (or energy more broadly) and economic output, in a country where 97% of the population has electricity access, follows directly from electricity's role as a physical input into the production process. Studies at the global and regional-level substantiate the existence of such a relationship: Campo (2013), investigating the relationship between energy consumption and GDP in 10 Latin American countries over the period 1980-2009, concludes that in Mexico an increase in energy consumption by 1% causes a 0.55% increase in long-run GDP. A literature focused on estimating the size of the shadow economy in transitioning/developing countries based on electricity consumption (Kaufman, 1996) furthermore attests directly to the potential of exploiting the electricity-output link to recover estimates of economic activity. Assessing different approaches to estimating total economic activity in developing countries Schneider and Enste (2000) conclude that electricity consumption serves as the most reliable available indicator. While composite indicator models often outperform any single indicator model (BOE, 2014) the electricity-GDP relation's strong theoretical foundation suggests that any loss in model performance and robustness associated with a focus on electricity consumption-related information only *may* be outweighed by the associated gain in model transparency and feasibility, i.e. the reduced scope for specification mining and need for costly data collection.
- *On a practical level*, electricity consumption already being monitored by the Comisión Federal de Electricidad[4] is available at a monthly frequency with only a 2 week lag at all administrative levels - electricity based-nowcasts of quarterly GDP are therefore potentially available with only a minimal time delay.

[4] The Mexican national utility company

Part III - Methodology

1. Statistical Models

Based on the existing literature and the rationale underlying the electricity-GDP relation three model 'types' can be identified (*see **Table-1)***.

Table-1: The Model Candidate Space

	Model	Description
Electricity	(1) Static electricity-based	$GDP_{X,T} = \boldsymbol{\beta}_{X,T}(Electricity_{X,T})$
	(2) Dynamic electricity-based	
Benchmark	(3) Autoregressive (AR) (4-lags) [1)]	$GDP_{X,T} = \sum_{n=1}^{4} \boldsymbol{\delta_n}(GDP_{X,T-n})$
GDP$_{X,T}$ and Electricity$_{X,T}$ refer respectively to GDP and electricity consumption in state X, quarter T. Intercepts, quarterly dummies and state fixed effects – included in all models - are suppressed and variables are differenced (see *Part III – Section 3*) ///[1)]Lag length chosen to minimize the AIC within a model candidate set		

The *static electricity based-nowcasting model **(1)*** in which GDP is regressed solely on electricity consumption is based on the assumption that the electricity intensity of output (captured by the β coefficient) is constant across states and stable across time, i.e. reflected in historical (as well as recent) data – an assumption which Feige and Urban (2003) conclusively reject for developing/transitioning economies: The reduced form relationship between electricity consumption and GDP has been found to be highly variable and context specific. While early studies find that globally a 1% rise in output is associated with a 1% increase in electricity consumption (Dobozi and Pohl, 1995) the income elasticity of electricity consumption ranges from 0.1 to 1.6 across different countries and time periods (Jaunky, 2006).

Following the modified electricity consumption method (Eilat and Zinnes, 2002) the *dynamic electricity based-nowcasting model **(2)*** relaxes this assumption and attempts to capture a structural relation between GDP and electricity consumption by accounting for factors that may affect the relation over time and states resulting in a dynamic electricity intensity coefficient (β). Drawing upon the existing literature, ***Table-2*** identifies four salient electricity intensity determinants alongside the methods chosen to incorporate them into the dynamic model.

Table-2: Electricity Intensity Determinants and Operationalizations

Electricity Intensity Determinants	Operationalization
Price-Induced Substitution Between Energy Sources	Interaction Term Real price[5] of electricity averaged over the preceding, current and ensuing quarter[6] × Electricity consumption
Weather	Interaction Term Seasonal dummies × Electricity consumption
Efficiency Changes Across Time	Time–Varying Estimation Window Models used to nowcast GDP in quarter T are estimated based on the information set, i.e. the estimation window, that would have produced the best nowcasts in the preceding 2 quarters[7]
State-Level Economic Structure	Semi-Pooled, State-Varying Energy Intensity Coefficient The electricity intensity coefficient is allowed to vary across four groups of states, identified based on states' average GDP/capita across time[8], but held constant within each group[9]

Finally, an *autoregressive (AR) model* ***(3)*** serves as an atheoretical benchmark against which to assess electricity-based nowcasting models (see *Part III – Section 3*). *In the interest of conciseness end of quarter estimates of GDP produced by the AR model are referred to as AR-based nowcasts despite not exploiting information such as electricity that is available more timely/frequently than GDP (see Footnote-3).*

2. The Data

The dataset comprises quarterly data at the level of Mexico's 32 states[10] over the period 2009 Q1 – 2014 Q1 (21 quarters)[11]. The dataset is complete (i.e. no missing data). ***Table-3*** describes the data series used.

[5] Deflated using the preceding quarter's national inflation rate

[6] To reflect factor input persistence, i.e. companies adjusting inputs based on price expectations shaped by prices in the recent past, the current period, and the near future

[7] Selecting estimation windows based on performance in the last *2* quarters mitigates the impact of 'random' shocks

[8] Absent sectorally disaggregated data, GDP/capita-based classifications (based on the assumption that states' GDP/capita over long periods – the training set - is informative about their structure) presents the best alternative

[9] Pooled forecast models generally outperform heterogeneous forecast models (i.e. models in which β is allowed to vary across all 32 states) even if poolability is rejected by classical statistical tests (Baltagi, 2008) – semi-pooled models are therefore preferred as they balance efficiency and bias considerations

[10] The ‚Federal District' is listed as a separate state

[11] While state-level GDP data is available over the period 2002Q1-2014Q1 (quarterly), state-level electricity consumption data is only available over the period 2009Q1-2014Q1 (monthly)

Table-3: Data Overview

Variables
Real Quarterly GDP (Pesos, Base year: 2008, non-deasonalised) Disaggregation: State-level aggregates
Quarterly Electricity Consumption, Volume (MWh, non-deasonalised) Disaggregation: State-level aggregates
Quarterly Electricity Price (Pesos/MWh, non-deasonalised) Disaggregation: State-level average
Monthly Business Confidence Indicator (ICP) (Index, non-deasonalised) Disaggregation: National-level (manufacturing, commercial and construction sector average)

Not listed are inflation and state population data used to deflate electricity prices/determine states' GDP/capita

3. Model Estimation and Evaluation

All three models are estimated employing ordinary least squares regression-based techniques appropriate for a panel of 32 states – state fixed effects account for time invariant heterogeneity between states while cluster robust-standard errors account for serial correlation and heteroskedasticity. GDP and electricity consumption are differenced (quarter-to-quarter % change) to ensure covariance stationarity[12] - the coefficient on electricity consumption (β) therefore represents the energy elasticity of income and the models generate nowcasts of quarter-to-quarter Mexican GDP growth.

Static models not accounting for efficiency trends, i.e. assuming a stability of the electricity intensity across time, are initially estimated using data over the period 2009 Q1-2012 Q1 (training set: 13 quarters) and subsequently updated recursively as the information set expands by 1 quarter with each GDP nowcast over the testing period (*see below*) - an expanding estimation window. Dynamic models incorporating efficiency trends are on the other hand, as detailed in *Table-2*, estimated using a moving, time varying estimation window (training set: ≤ 13 quarters). To ensure that the relative performance of the electricity-based models and the AR model is not driven by differences in the estimation techniques employed, the AR model is *unless otherwise stated* estimated (i) based upon a pooled sample of all states and an expanding estimation window when serving as a benchmark for the static models and (ii) based upon a semi-pooled sample of states and a time-varying estimation window when serving as a benchmark for the dynamic models.

[12] The inclusion of state-level fixed effects, the choice standard errors and the differencing of the GDP and electricity data series is based on a series of diagnostic tests (at the 5% significance level) – respectively, a robust Hausman test of the random effect hypothesis; tests for cross-sectional dependence, group-wise heteroskedasticity and within panel autocorrelation; and an Im-Pesaran-Shin (IPS) unit root test of quarterly GDP

Model performance is assessed by nowcasting state-level GDP over the period 2012 Q2-2014 Q1 (testing set: 8 quarters)[13]using information available to policy makers at the point of each nowcast production (pseudo real-time simulation). National nowcasts are produced by aggregating state-level nowcasts[14]. To ensure that the results are not an artifact of the choice of testing set period, all results are validated over 5 four-year subsets of the testing set[15].

Model evaluation is based on the out-of sample Root Mean Squared Error (RMSE) of the state and national-level nowcasts. In light of the Government's focus on obtaining a 'Proof of Concept' to serve as an impetus for a further refinement of the approach, the electricity consumption-based nowcasting models' relative rather than absolute performance, which is unlikely to be optimized given the eschewing of more complex estimation techniques in the interest of model transparency[16], is adopted as the focal point, i.e. the metric of interest is the ratio of models' RMSE relative to the AR model's RMSE.

[13] A training/testing set process reduces the sample size – similar model performance rankings are however obtained using an alternative, sample-size preserving procedure (Leave-One-Out-Cross-Validation)

[14] Regional aggregation-based models have been shown to outperform national models (BOE, 2014)

[15] The results are validated over 5 four-year testing sets, e.g. models are assessed over the period 2012 Q2 – 2013 Q1, over the period 2012 Q3 – 2013 Q2, etc. In each case the training period is extended up to the starting date of the testing set while information after the ending date of the testing period is not used

[16] While the existing literature suggests that more complex techniques improve absolute model performance there is no presumption that relative model performance is affected

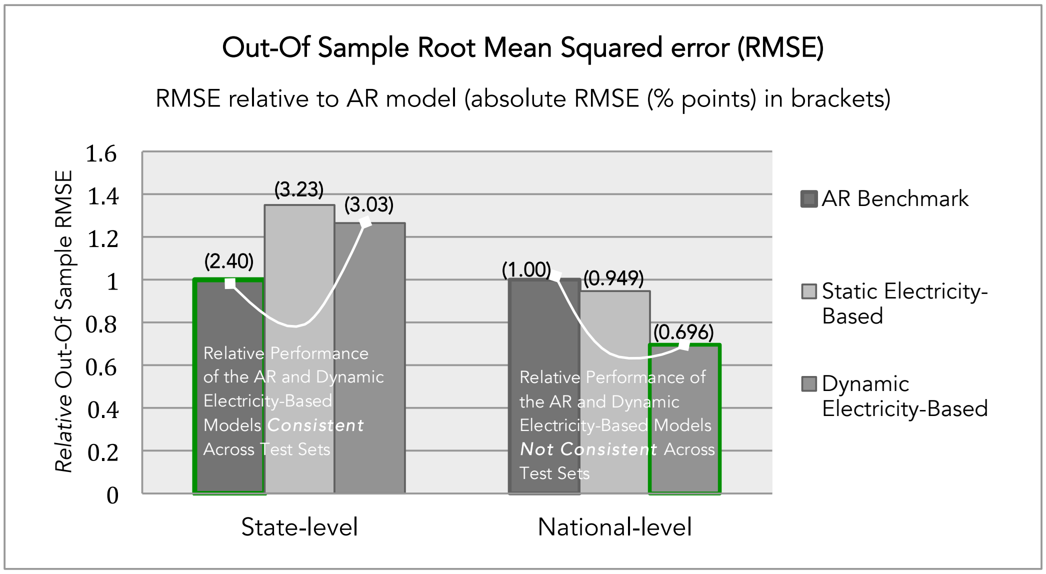
Part IV – Results

1. Baseline Results

1.1. *Relative Performance of the AR and Electricity-Based Models*

Figure-2 displays the static and dynamic electricity-based nowcasts' relative RMSE (the absolute RMSE is displayed in brackets[17]) assessed over the 8 quarter testing set (see the *Appendix*, ***Figure A-C*** for the underlying nowcasts).

Figure-2: Relative (and Absolute) RMSE of the AR and Electricity-Based Nowcasts



The AR model refers to the 'best' AR model - estimated using a semi-pooled sample of states and a time-varying estimation window - as the most stringent benchmark (see *Part III, Section 3*)

In terms of the relative performance of the static and dynamic electricity-based model, the dynamic model outperforms the static model at both the state and national-level – a finding that is confirmed across the testing subsets (results not shown) and derives largely from the usage of time-varying rather than expanding estimation windows to capture electricity intensity variation across time[18]. This result attests to the importance of accounting for the weakness of the *unmediated* GDP-electricity relation[19] in Mexico – a weakness stemming from the significant structural shifts, both endogenous and policy-driven, affecting electricity consumption in Mexico (ABB, 2011). *In light of these conclusive findings all further analysis proceeds on the basis of the dynamic rather than static electricity-based model.*

Comparing the performance of the dynamic (i.e. best) electricity-based model and

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[17] The models' absolute RMSE needs to be interpreted in light of the discussion presented in *Part III, Section-3*

[18] The other three energy intensity determinants incorporated into the dynamic model (see ***Table-2***) also proved significant in improving model performance

[19] The raw correlation between national quarter-to-quarter changes in electricity consumption and GDP is 0.0830

the AR model yields less consistent findings: While the AR model consistently outperforms the electricity-based model at the state level, relative performance at the national-level varies across the testing subsets, i.e. the superior performance of the electricity-based model (see ***Figure-2***) is not confirmed across the different testing subsets. An analysis of the magnitude *and* distribution of the nowcast errors at the state-level[20] suggests that the AR and electricity-based model perform well under different conditions - as conditions evolve across time relative model performance at the national-level, i.e. the relative size of the aggregated state-level nowcast errors, changes. An exploratory analysis of potential relative model performance determinants points to the role of economic stability and economic structures (see the *Appendix*, ***Figure-F*** for detailed results):

- *Economic Stability:* The AR model performs better in states with stable rather than unstable growth over the testing period and vice versa for the electricity-based model which outperforms the AR model in economically unstable states - a result in line with the conclusion of the BOE (2014).
- *Economic Structure:* The AR model performs better in richer, i.e. higher GDP/capita, than poorer states and vice versa for the electricity-based model[21]. Based on the *hypothesis* that states' GDP serves as a proxy for their economic structure whereby richer states tend to move from primary/secondary sector activities towards less energy intensive tertiary activities[22], this result is consistent with the argument that the electricity-based model performs best where electricity is a significant input into the production process, i.e. in energy intensive states.

1.2. <u>Model Averaging</u>

A significant amount of literature suggests that model averaging may produce nowcasts which perform favorably relative to nowcasts based on the construction and selection of one single best model in cases where the individual models perform well under different conditions, i.e. exploit different sets of information (Dolega, 2010)[23].

In the model examined (see ***Figure-3***) the weights assigned to the state/national-

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[20] Over the 8 period testing set for instance the AR model has a smaller RMSE but in contrast to the electricity-based model's symmetrically distributed errors the errors are positively skewed resulting in larger national-level errors

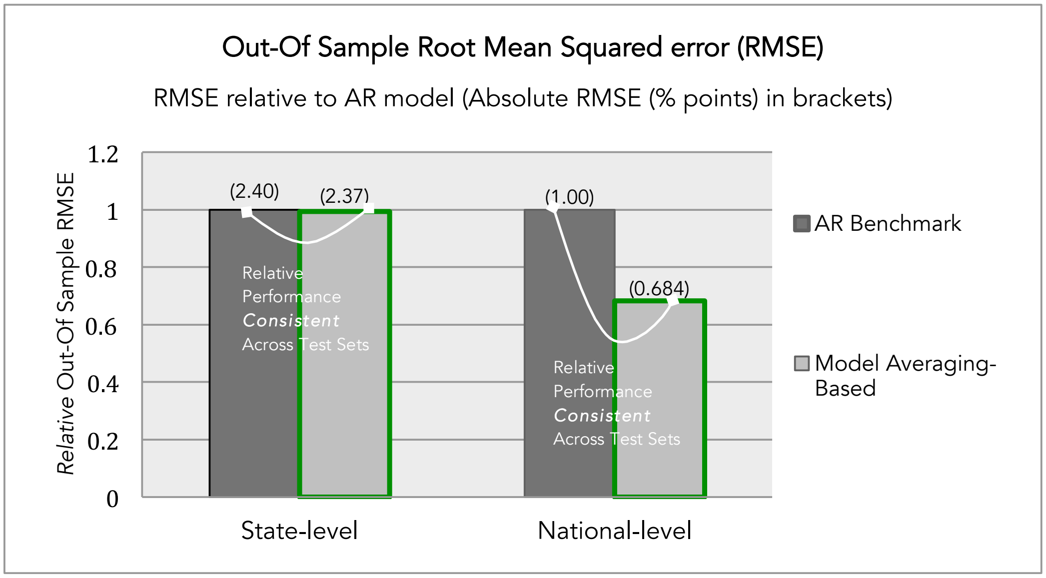
[21] This finding holds even when controlling for growth volatility which may be correlated with states' GDP/capita

[22] While alternative interpretations of the findings cannot be ruled out the results cast doubt upon two prominent interpretations - poorer states being characterized by a larger or more rapidly growing informal sector or being characterized by a higher prevalence of energy theft not captured in electricity statistics - which would imply that the link between electricity consumption and GDP is weaker rather than stronger in poorer states

[23] The superior performance of a model averaging approach has been linked to the optimal use of *all* available information, i.e. the pooling of states in the estimation of model parameters ensures parameter stability which is combined with state specific information in the weight selection process

level AR and electricity-based nowcasts for the current quarter are selected based on model performance in the recent past i.e. the model adopts the set of weights that would have minimized the RMSE in the last 2 quarters[24]. In the case of state-level nowcasts the weights, varying by state, are chosen based on state-level RMSE while for national-level nowcasts the weights are based on national-level RMSE.

Figure-3: Relative (and Absolute) RMSE of the AR and Model Averaging-Based Nowcasts



The model averaging based-model outperforms the AR and electricity-based model, i.e. outperforms the AR model as the best model at the state level in the 8 quarter testing period (*and* the dynamic electricity-based model as the best model at the national-level) – a finding that is consistent across the testing subsets. The weights selected - on average more weight is placed on the AR model in states which are stable and characterized by a higher GDP/capita - moreover lend credibility to the two hypotheses regarding relative model performance explored in *Section 1.1*.

While the reduction in RMSE relative to the AR model at the state-level (and relative to the dynamic electricity-based model at the national-level) is marginal, given that the selection of weights is purely backward looking, i.e. does not incorporate insights into states' stability and economic structure in the current quarter (see *Part IV, Section 3* for a discussion of challenges associated with such an extension of the model) these results must be seen as a lower bound on the RMSE reductions that could potentially be attained by a model averaging-based approach.

[24] Weights are selected from within a set of discrete weights (ratio of weight on AR to weight on electricity based nowcast: 1:0, 0.75:0.25, 0.5:0.5, 0.25:0.75, 0:1). An alternative selection process - weights are based on the inverse of each model's RMSE in the preceding 2 quarters, was also explored (*see Part V, Section III*)

2. Extensions

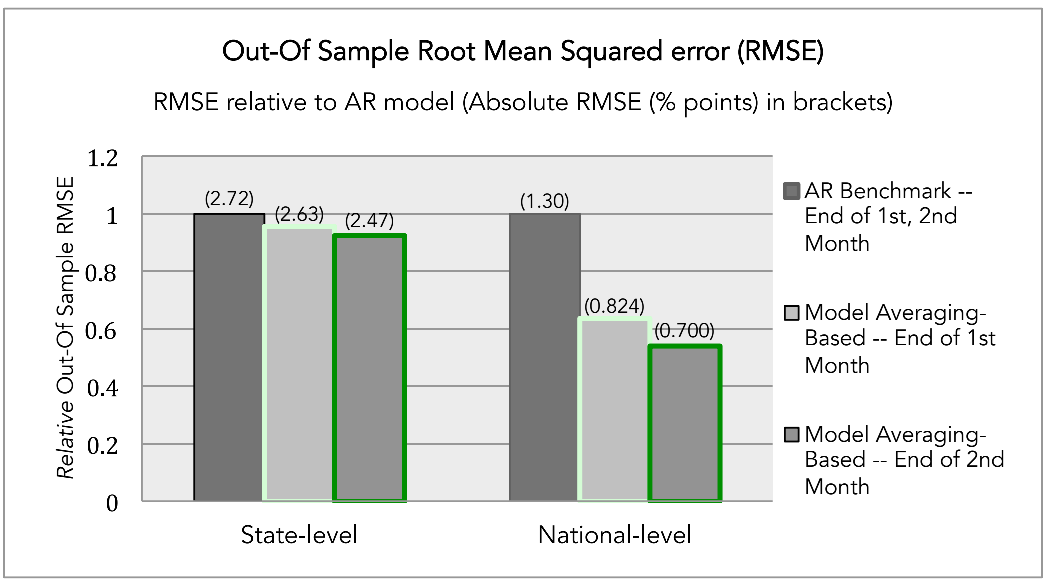
2.1. *Short-Term Forecasts*

The availability of electricity data at a monthly frequency provides an opportunity for producing short-term forecasts of quarterly GDP growth at the end of a quarter's 1st and 2nd as monthly electricity data becomes available.

To model the information available to policy makers at the time of forecasting, the AR model and electricity-based models are estimated based on GDP data starting from the second-last quarter, e.g. information on 2011 Q4 GDP is the latest available information at the end of the 1st and 2nd month in 2012 Q2 given GDP publication lags (see *Figure-1*). The electricity-based model additionally exploits data on monthly electricity consumption in the 1st (and 2nd) month by using a 'bridge equation' to generate estimates of quarterly electricity consumption based on these monthly figures[25].

Figure-4 illustrates the RMSE of the short-term forecasts produced by the AR model and the model averaging-based model, i.e. the averaging of AR and electricity-based forecasts[26].

Figure-4: Relative (and Absolute) RMSE of the AR and Model Averaging-Based Forecasts



The incorporation of monthly electricity data ensures that the model averaging-based forecast outperforms the AR-based forecast and improves from month-to-

[25] Specifically, using an AR model, chosen to minimize the AIC, monthly electricity consumption is forecast at the end of the 1st/2nd month over the remainder of the nowcast quarter to obtain an estimate of quarterly electricity consumption (see the *Appendix* – *Figure D*). This estimate is subsequently used as a regressor in the nowcasting model to generate an estimate of current quarter GDP growth. For more details see BOE (2014)

[26] The model averaging-based model outperforms the purely electricity based model in terms of forecast RMSE

month (converging to the nowcast at the end of the 3rd month) as new data becomes available. While model performance deteriorates as the information set is restricted to include only 1st month rather than end of quarter electricity data *(compare Figure-3 and Figure-4)* a further refinement of the model may provide policymakers with *informative* early signals of states' growth.

2.2. Modifying the Data Release Schedule

In light of the arguments in favor of a single-indicator model (see *Part II)* an expansion of the nowcasting model's covariate set needs to strengthen model performance while preserving the approach's feasibility – the incorporation of national business confidence survey data (*see Table-3)* presents such an expansion:

- Business confidence survey data is forward looking and therefore informative for both nowcasting *and* short-term forecasting – the reason behind the inclusion of survey data in nowcasts produced by other countries (Diron, 2002)
- Business confidence survey data is already available in Mexico at a monthly frequency with only a 1.5 month lag (as compared to a 3 month lag for other data) (see *Figure-1*)
- The expansion and acceleration of survey data collection is relatively more feasible than the expansion and acceleration of hard economic indicator collection such as employment given the scope for significant survey automatisation – the recent expansion of Mexican business survey data collection from the national to the state-level[27] attests to this

To explore the potential gains associated with accelerating the collection of business confidence data and including it in the information set the model averaging technique is employed to combine AR, dynamic electricity and national business confidence-based GDP nowcasts *assuming that confidence surveys and electricity consumption data are released concurrently* (i.e. with a 2 week lag).

The results (see the *Appendix – Figure E*) suggest that business confidence data marginally improves the performance of the averaging model at the state/national-level – while the magnitude of resultant RMSE reduction is small an incorporation of more granular state-level business confidence survey data would likely generate a more substantial improvement in model performance.

[27] The state-level business confidence data is not yet publicly available

3. Applying the Findings to Mexican Municipality Data

All the data used in the development of the models assessed in the preceding sections *is theoretically* available (see *Footnote-2*), at the same level of disaggregation, for Mexico's 2438 municipalities - the model averaging-based nowcasting model is therefore directly applicable to Mexico's municipalities.

Electricity data at the municipality level is theoretically available over the period 2006 Q1- 2014 Q3 while 5-year GDP estimates are available in 2005 and 2010. The lack of yearly GDP data precludes a *re-estimation* of the model at the municipality-level. Instead, the dynamic model, including state-level fixed effects and semi-pooled coefficients, could be directly applied to municipality level electricity data. Yearly nowcasts over the period 2005-2010 aggregated to produce 5-year nowcasts of GDP in 2005 and 2010 would serve to validate the model.

Part V - Policy Implications and Recommendations

1. Significance of the Results

The significance of the findings for policy makers seeking to target policy on the basis of the nowcasts can be captured by analyzing the likelihood that a nowcasting model correctly assesses whether a state's GDP has fallen or grown in any given quarter thereby providing an informative policy signal:

- At the end of the quarter, the model-averaging approach correctly nowcasts the sign of states' GDP growth 92.3% of the time compared to 80.6% for the AR benchmark model. If national business confidence data is released concurrently with electricity consumption data a model averaging-based nowcasting model exploiting all available information correctly nowcasts the sign of the state's GDP growth 93% of the time.
- At the end of the 1st/2nd month of a quarter the model-averaging approach correctly forecasts the sign of a state's GDP growth 84% and 89% of the time respectively compared to the AR benchmark model which correctly forecasts the sign of the states' GDP growth 73% of the time.

While the results likely represent an upper bound on the models' absolute performance given that the period investigated was characterized by a stability of Mexican growth the results regarding relative model performance, i.e. the gains associated with moving from an AR-based model to a model averaging-based model incorporating electricity (and confidence) data are economically significant and suggest electricity-based modeling as a promising avenue for further research.

The significance of the results moreover extends beyond Mexico given that the problem of infrequent and out-of date economic data is faced by a large number of developing *and* developed countries - prior to 2014, estimates of US state-level GDP were for instance released annually with a 6-month lag (BEA, 2014). The unexacting data requirements of the approach coupled with an understanding of the conditions under which electricity information is most informative provide the basis for applying the results to other countries. The finding that electricity-based models on average optimally use a 5-quarter estimation window (whilst the AR model optimally uses a 10-quarter window) moreover suggests that the electricity-based model can be applied even in the absence of long historical time series without significantly compromising model performance.

2. Policy Recommendations

Strengthening the data collection and analysis capacities of the Government will be critical to the further development of the nowcasting models:

- Building upon the Mexican Open Data Initiative a focus should be placed on making economic indicators accessible to researchers in a timely manner, i.e. ensuring that data such as electricity consumption and state-level business confidence data *is* made available when officially released.
- Choices regarding the formatting of data collected at all levels of government and publicly owned organisations should be informed by an awareness of the data's *potential* usage as indicators of economic activity: Aggregating electricity consumption data by usage sector (primary, secondary, tertiary) rather than user type[28] would for instance allow for the construction of separate output nowcasts for each sector to be aggregated to produce state-level GDP nowcasts - an approach which would capture the variation in electricity intensity across sectors.
- The collection of data that is informative about economic conditions should be expanded and improved with an emphasis upon data whose collection is expandable at minimal costs and which promises the greatest gain in model performance – the acceleration of forward looking business confidence survey collection present one option as does the automatisation of electricity consumption data collection which is currently based on manual metre readings, a process prone to produce erroneous statistics.

3. Further Research

While the results suggest that changes in electricity consumption are informative about economic growth the results need to be validated over a longer time period to ensure that they are robust to structural changes across time and further research is needed to improve the absolute performance of an electricity-based nowcasting model, i.e. to minimize the model's absolute RMSE:

- The considerable improvements in model performance associated with moving from a static to a dynamic electricity-GDP relation suggest that other plausible energy intensity determinants should be explored - the literature suggests factors such as business cycles, a consideration supported by the divergence between Mexican electricity consumption and GDP during the recent economic crisis (ABB, 2011). Furthermore the tentative operationalization of these factors

[28] User type classifications include e.g. "Domestic for locations with warm weather", "General Demand", etc. The availability of other electricity related data streams at the sector level of aggregation suggest that such an aggregation *is* feasible

should tested and refined, examples of such refinements could include a more realistic modeling of price-induced substitution effects that takes into account state-level prices of alternative energy sources (electricity substitutes).

- Adaptations of the process used to select the optimal estimation window length and the optimal weights used in the model averaging process are likely to result in further improvements in model performance. The process of choosing the weights should for instance incorporate information on current quarter conditions that are informative about the relative usefulness of AR and electricity-based nowcasts such as economic stability. Integrating such information will require a more exhaustive investigation of relevant factors and an identification of variables, available in a timely manner, able to capture these conditions: Trading partner's growth, where released more frequently than Mexican data, may for instance serve as potential source of information abut current quarter volatility in Mexico. An analysis of the UK's experience with nowcasting (BOE, 2014) suggests that choosing optimal weights based upon the identified broad set of indicators would require a significant degree of flexibility in responding to the information.
- While the assessment of the models has focused on their ability to nowcast formal sector economic output, electricity consumption may be more informative about total economic activity, i.e. the sum of formal and informal activity. This should be explored as a promising alternative use of the model given that 30% of the Mexican economically active population works in the informal sector.

Part VI - Conclusion

Based upon the results presented in *Part III* electricity-based nowcasting, in particular when embedded in a model averaging approach, promises to help the Mexican Government address the lack of frequent and timely estimates of economic activity by providing both quarterly growth nowcasts and early growth forecasts. The policy recommendations and suggestions for further research highlighted in Part V present a starting point from which to transform the results into a robust nowcasting model providing policy makers with near real-time information about economic conditions allowing for the most effective targeting of polices at the national, state (and municipality) level.

Appendix

Figure-A: AR and Dynamic Electricity-Based Nowcast

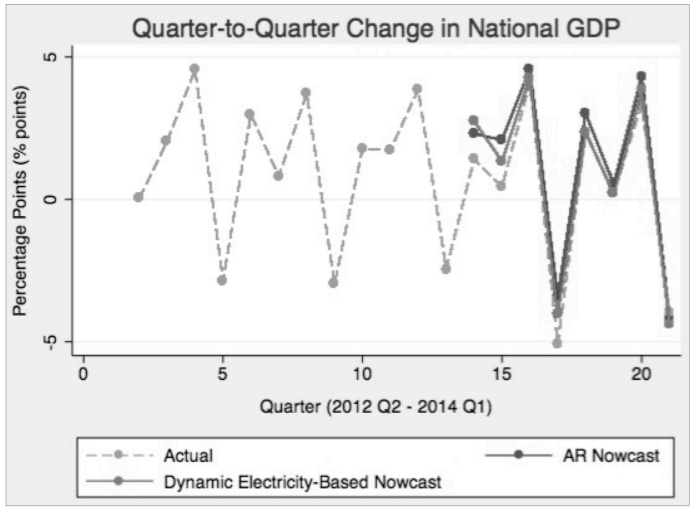


Figure-B: AR-Based Nowcast (95% Confidence Interval)

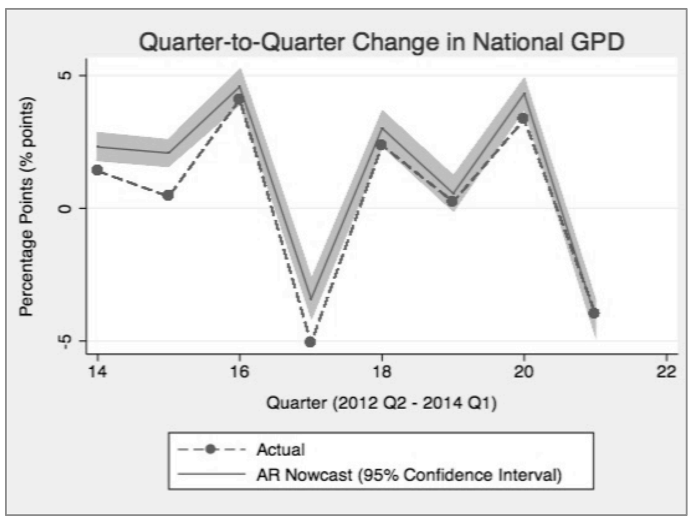


Figure-C: Dynamic Electricity-Based Nowcast (95% Confidence Interval)

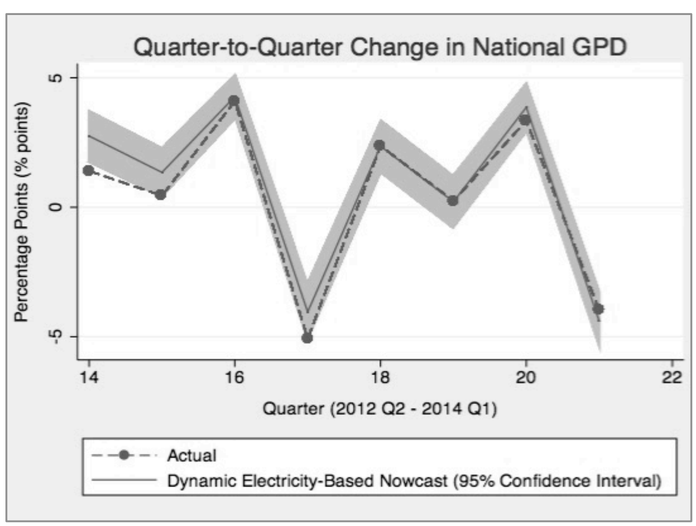


Figure D: Quarterly Electricity Consumption Forecasts Based on 1st/2nd Month Electricity Consumption

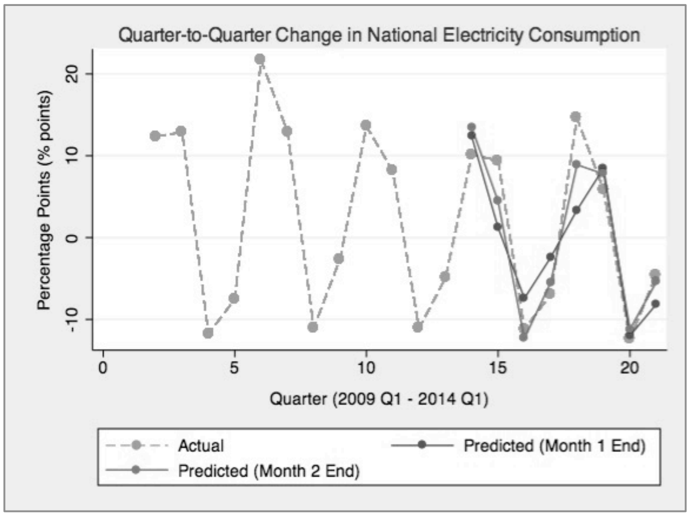


Figure-E: Relative (and Absolute) RMSE of the AR and Survey Augmented Model Averaging-Based Nowcast

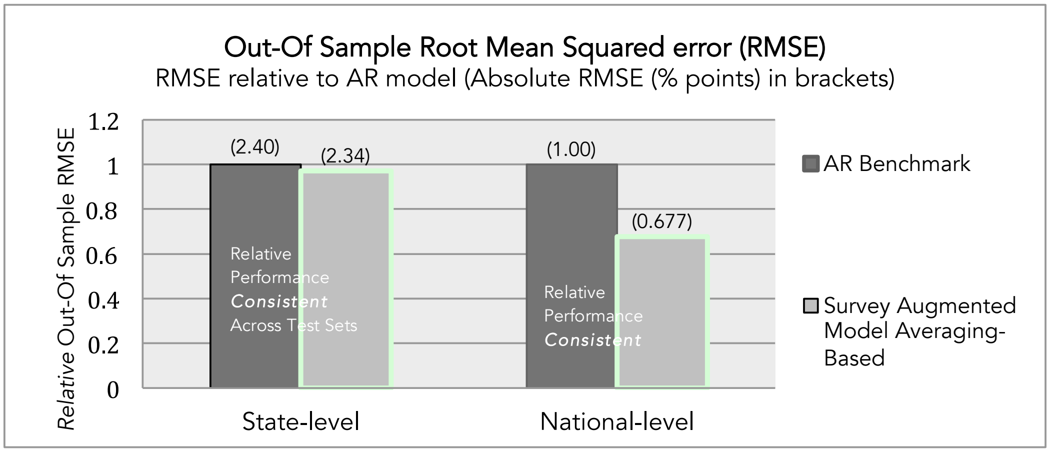
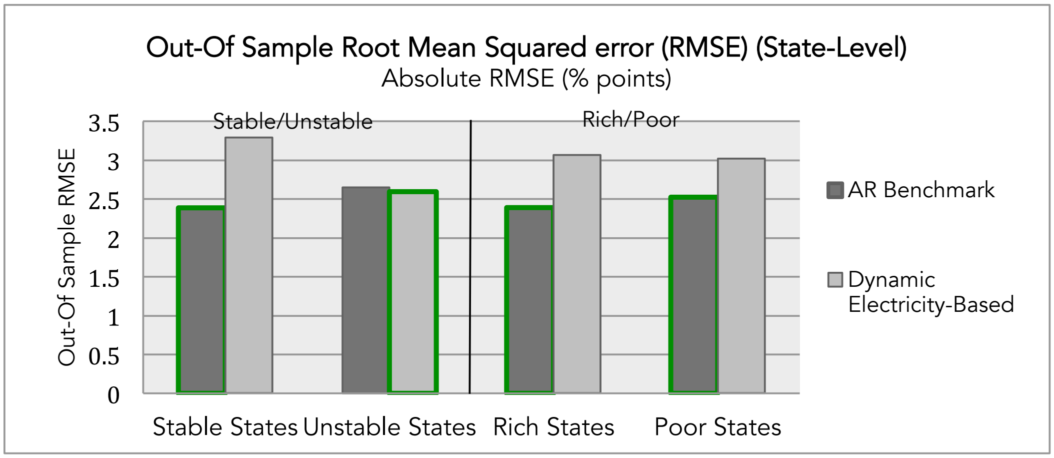


Figure-F: Relative (and Absolute) RMSE of the AR and Dynamic Electricity-Based Nowcast in Stable/Unstable, Rich/Poor states



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All the data was obtained directly from the Office of the President of Mexico with the exception of the Business Confidence and Population Data which was obtained from the *Instituto Nacional De Estadistica Y Geografia* (www.inegi.org.mx).

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