The Causality between Energy Consumption and Economic Growth for China in a Time-varying Framework

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ABSTRACT

Extending existing studies based on constant structure, we adopt a time-varying approach to study energy consumption and GDP causality for China in a context of industrialization and urbanization. We find that in light of structural change, China's energy consumption is trend-stationary and thus forms no cointegration with GDP. Further, the relationship between energy consumption and GDP is two-way causal and has been decreasing in strength over time. Finally, industrialization and urbanization, especially the former, have limited effects on energy consumption, suggesting the decreasing energy intensities in individual sectors, instead of structure shift between sectors, as the main reason for China's decreasing energy intensity over the years.

Keywords: Energy consumption, Economic growth, China

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1. INTRODUCTION

The importance of the relationship between energy consumption and economic growth has been widely acknowledged, as evidenced by the extensive line of studies following Kraft and Kraft (1978). This issue is particularly important for China. As the largest developing country, China has recently achieved its status as the second largest economy and the largest energy user worldwide (International Energy Agency, 2010). Under the pressure to reduce Greenhouse Gases (GHG) emission, the challenge to balance between economic growth and energy consumption is even greater, especially when China is in a stage of industrialization and urbanization (Lin and Liu, 2010). This challenge calls for further understanding of the relationship between energy and growth.

Studies on this issue for China first appeared in the 1990s (Tang and La Croix, 1993; Huang, 1993a; Chan and Lee, 1996), and have since grown steadily in number. We provide in Table 1 a brief summary of studies that have emerged since 2000 focusing on China or covering China within a group of countries. Based on varying sample periods, they examine how different types of energy consumption, from aggregate national to disaggregate regional, interact with economic growth in causality. These studies take a number of econometric approaches, with Granger causality as the dominant type, followed by innovation accounting (impulse response function or forecast error variance decomposition), mostly in an error correction model (ECM). Possibly affected by the different samples and methods, the causality findings are mixed. Earlier studies (Shiu and Lam,

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Table 1: Literature on the Relationship between Energy and Growth for China

Authors	Year	Journal	Type	Sample	Method	Causality
Shiu and Lam	2004	EP	elec.	1971–2000	Granger in ECM	energy to GDP
Wolde-Rufael	2004	EE	elec./ Shanghai	1952–1999	Granger in VAR	energy to GDP
Soytas and Sari	2006	JPM	total	1971–2002	Granger in VAR and GIR in VAR	energy to GDP, marginal
Zou and Chau	2006	EP	oil	1953–2002	Granger in ECM	energy to GDP
Chen et al.	2007	EP	elec.	1971–2001	Granger in ECM	none
Yuan et al.	2007	EE	total	1978–2004	Granger in ECM and HP filter	energy to GDP
Yuan et al.	2008	EE	total and disaggregate	1963–2005	Granger in ECM	GDP to energy
Lee and Chang	2008	REE	total	1971–2002	Granger in ECM, panel	energy to GDP
Zhang and Cheng	2009	EcE	total	1960–2007	Granger in VAR and GIR in VAR	GDP to energy
Li et al.	2011	EP	total/ regional	1985–2007	panel DOLS	energy to GDP
Akkemik and Goksal	2012	EE	total	1980–2007	Granger in ECM, panel	bi-directional
Bloch et al.	2012	EE	coal	1965–2008	Granger in ECM GIR/GFEVD in ECM	bi-directional
Li and Leung	2012	EP	coal /regional	1985–2008	Granger in ECM, panel	varying on regions
Michieka and Fletcher	2012	EP	coal	1971–2009	Granger in VAR	GDP to energy
Yalta and Cakar	2012	EP	total	1971–2007	Meboot VAR	none
Zhang and Xu	2012	EE	total /regional /sectoral	1995–2008	Granger in ECM, panel	bi-directional

Notes:
a. For column Journal, EcE, EE, EP, JPM, REE stands for Ecological Economics, Energy Economics, Energy Policy, Journal of Policy Modeling, and Resource and Energy Economics respectively.
b. Column Type gives the particular type of energy consumption, elec. stands for electricity consumption, total for total energy consumption. If energy consumption is not for national level, we give the particular level after "/".
c. For column Method, DOLS, GIR/GFEVD, HP stands for dynamic OLS, Generalized Impulse Response/Generalized Forecast Error Variance Decomposition, and Hodrick-Prescott respectively.
d. For studies involving more than one level of energy consumption, causality result is based on the aggregate level finding.

2004; Wolde-Rufael, 2004; Soytas and Sari, 2006; Zou and Chau, 2006) almost unanimously suggest a unidirectional causality from energy to growth. Causality from growth to energy and bi-directional causality have also emerged more recently (Yuan et al., 2008; Zhang and Cheng, 2009; Akkemik and Goksal, 2012; Bloch et al., 2012).

In this paper, we revisit the relationship between energy consumption and economic growth for China out of two motivations. As the first motivation, while existing studies have offered important insights into this relationship, the issue has generally been studied under the implicit assumption of a constant econometric structure,[1] giving little consideration to the possibility of structural change/break in the relationship between energy and growth. The assumption of constant

1. The terms "structure" and "structural" are used repeatedly in the paper, unavoidably in differing contexts. While the "structure" here applies to the econometric dimension, "structure" or "structural" later sometimes refers to the makeup of economy, such as the level of industrialization or urbanization. The distinction between econometric and economic dimension should be borne in mind when reading the paper.

econometric structure can be strong in this case. Over the recent decades, tremendous change has been witnessed in the Chinese economy, not only affecting the size of the economy, but also its structure in many important dimensions.[2] As documented in Altinay and Karagol (2004), Lee and Chang (2005), and Balcilar et al. (2010), the influence of changing economic structure and possibly even economic regimes, can result in the change of causality between energy and growth. Therefore, it is important to account for structural change when evaluating the energy-growth relationship, especially for the case of China.

As the second motivation, we argue that beyond the bivariate causal relationship between energy consumption and economic growth, the channel of causality is also important, but has not been adequately addressed in the literature. By 'channel of causality', we mean the particular routes for the causality to take effect. For example, consider an energy–constrained economy, given a unidirectional causality from energy to growth, one way to explore the causal channel is by asking which sector of the economy energy consumption impacts most. An answer to this question will help us design an efficient industrial policy, so that energy conservation may be achieved with the least possible harm to economic growth. Clearly, the particular channel depends on the structural view we take and can be represented by the resulting structural variables we use. Two recent examples using structural variables are Liu (2009) and Feng et al. (2009). Liu (2009) studied urbanization (population structure) in relation to energy consumption and economic growth. Feng et al. (2009) studied the share of tertiary industry (economic structure) in relation to energy intensity. In fact, urbanization and industrialization are the two processes widely believed to have shaped China's growth and have fundamental effects on China's energy consumption and GHG emission. We take the research one step further by modeling both industrialization and urbanization (or to be precise, the structural shifts associated with either process) in a unified system, so to reveal their related yet differing effects on energy and growth.

In line with related literature, we model the energy-growth causality in a Vector Autoregression (VAR) system. Industrialization and urbanization are included in the system to evaluate the channels of causality upon energy consumption and economic growth. Our VAR-based analysis departs from related studies in two aspects. First, we initiate the empirics by first testing the individual data series for structural stability, and given evidence of instability, we embed the VAR system in a rolling window framework to examine time-variation in system dynamics. Second, following Swanson and Granger (1997), we do the VAR identification using the data-driven Directed Acyclic Graphs (DAG).

The paper proceeds as follows. Section 2 introduces the conceptual framework and data. Section 3 tests data stationarity subject to structural change. Section 4 describes the VAR-based approach for system dynamics analysis. Section 5 presents the results and discussions of system dynamics analysis. Finally, Section 6 concludes the paper.

2. CONCEPTUAL FRAMEWORK AND DATA

Existing studies often use an aggregate production function to provide a sensible conceptual framework for multivariate analysis of the energy-growth relationship. As one recent example, Yuan et al. (2008) consider the following three-factor production function:

2. From 1963 to 2010, China's GDP has increased by 30 times and its levels of industrialization and urbanization have increased from 59.4, 16.8 to 89.9, 49.9 respectively. See more details in Section 2.

$$Y_t = f(K_t, L_t, E_t) \tag{1}$$

where Y_t, K_t, L_t, E_t represent output, capital, labor, and energy consumption respectively for time t. The conceptual production function is intended to supply a set of relevant variables, that may or may not be endogenously related, but not to dictate a specific nature/direction of causality relationship. In this paper, to incorporate the structural features of the Chinese economy, we consider an alternative framework by first noting that following the popular index decomposition approach for energy intensity (see Ma et al., 2010 for description), energy consumption can be re-expressed as a function of output and energy intensity:

$$E_t = Y_t \cdot EI_t = Y_t \cdot \left(\sum_{i=1}^{n} S_{it} \cdot I_{it}\right) \tag{2}$$

where E_t and Y_t are as defined above, EI_t stands for aggregated energy intensity of the economy, S_{it} the output share of the i_{th} sector, and I_{it} the corresponding energy intensity of the i_{th} sector. Unlike the production function in equation (1), E_t is shown to be a complete decomposition consisting of Y_t, S_{it}, and I_{it}. To focus on the structural feature of the Chinese economy, we consider explicitly in our multivariate system S_{it} while we do not include I_{it} directly into the system since it is inherently unobservable. This treatment essentially implies the equation below:

$$E_t/Y_t = EI_t = f(S_{1t}, \ldots, S_{nt}) \tag{3}$$

If we compare this equation to equation (1), then sector energy intensity I_{it} is comparable to the technology of the production and does not show up in the above energy intensity function. The benefit of this treatment is, in the following multivariate analysis, we can focus on output, energy consumption, and sector output share(s) in a compact system without having to include sector energy intensities. Further, we show in Section 5 that while I_{it} is not modeled explicitly in the system, we can still draw inference on I_{it} to certain degree given that equation (2) is a complete decomposition and I_{it} is the only dimension not addressed directly in our empirical system.

For the specific definition of sector output share(s), we adopt the share of nonagricultural sector in the economy to reflect the broad definition of industrialization in China. While not directly available from the equation above, urbanization, the population structure, is another structural variable widely believed to shape China's economic and social development pattern and thus is also included in the system. The joint consideration of industrialization and urbanization is designed to capture their differing and related effects on energy consumption and economic growth relationship.

In sum, we consider a four-variable VAR system (described in detail in Section 4) for the interaction between energy consumption and economic growth. In addition to the two indispensable variables for energy consumption (EC) and economic growth (GDP), we further include the share of GDP due to nonagricultural sectors (IND, secondary and tertiary sectors combined) and the share of population living in cities and towns (URB) to represent industrialization and urbanization in the system, especially the structural shifts associated with either process. It is important to recognize that IND and URB thus defined capture the *relative* weights of nonagricultural GDP and urban population versus their respective counterparts (agricultural GDP and rural population), not the absolute scales. In addition, the IND defined here is a broad measure for industrialization and is used to capture the baseline feature of the Chinese economy. We later present an alternative set of analysis based on a narrow IND defined over the secondary industry only in subsection 5.6.

Data for the four variables is sampled for the years from 1963 to 2010 and is taken from the National Bureau of Statistics of China. In particular, GDP is represented by real Gross Domestic Product per capita, and EC by energy consumption per capita. We specify the two variables in per capita terms to factor in the effect of population change. Compared to the approach of including population directly, the per capita specification allows for a more compact system.

The data are plotted in Figure 1. Shown in Panel A, GDP appears to follow a relatively smooth pattern of nonlinear (seemingly exponential) growth, EC appears to follow first a trend of linear growth up to year 2000, then another phase of linear growth at a different rate. As to the two structure variables shown in Panel B, IND, despite fluctuations, maintains a steady trend of linear growth during the whole sample period; URB appears to have experienced two periods of accelerated growth, with turning points around the late 1970s and mid-1990s. The level of industrialization in the Chinese economy was as high as 90% in 2010, while the level of urbanization is roughly 50%. Due to its lower starting point, URB has grown somewhat faster than IND over the sample period, and may continue to do so over the near future.

3. TESTING FOR STATIONARITY AND STRUCTURAL BREAKS

Prior to considering the modeling for system dynamics, it is important to test the data on stationarity. We start by testing the four series on stationarity using Augmented Dickey Fuller (ADF), Phillips and Perron (PP), Dickey Fuller-GLS, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The overall results suggest all four series to be nonstationary, either I(1) or I(2), and the results from ADF and PP are given in Table 2.

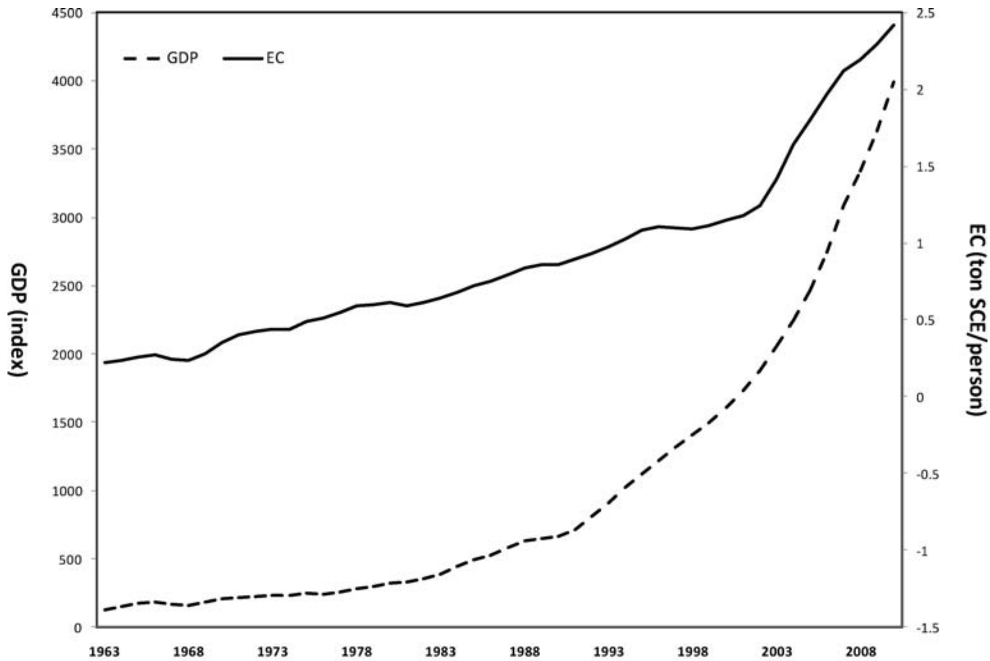
While the results from standard unit root test are largely consistent with previous studies, from Figure 1, it might be inferred that there is a possible structural break in EC shortly after 2000. As China is widely understood to have undergone substantial change in both its scale and structure, the possibility of structural change is hard to dismiss. We thus formally test for structural break in all the four series. The method we use is the one due to Zivot and Andrews (1992). The Zivot and Andrews (ZA henceforth) method tests on stationarity of a series in the presence of structural break. ZA test is not the only one in this regard. Perron (1989) proposed the test for stationarity when structural break is present. Given a series being nonstationary based on tests considering no break, both ZA and Perron tests can further determine whether the series is nonstationary with unit root, or trend-stationary with break point. The difference between two tests is, Perron test needs prior information on the location of break point while ZA test does not. In other words, ZA test is applicable when break point is endogenous.[3] Given the lack of break point information here, the use of ZA test is justified. Two recent examples of ZA test in the energy literature are Altinay and Karagol (2004) and Lee and Chang (2005).

An extension of Dickey-Fuller type test, the ZA test uses one of its three specifications to allow for either a break in the intercept, a break in the slope, or a break in both the intercept and slope. In this study, based on visual inspection of data as in Figure 1, we restrict attention to the two cases of break in slope, and break in both intercept and slope. These tests require estimating the following equations respectively:

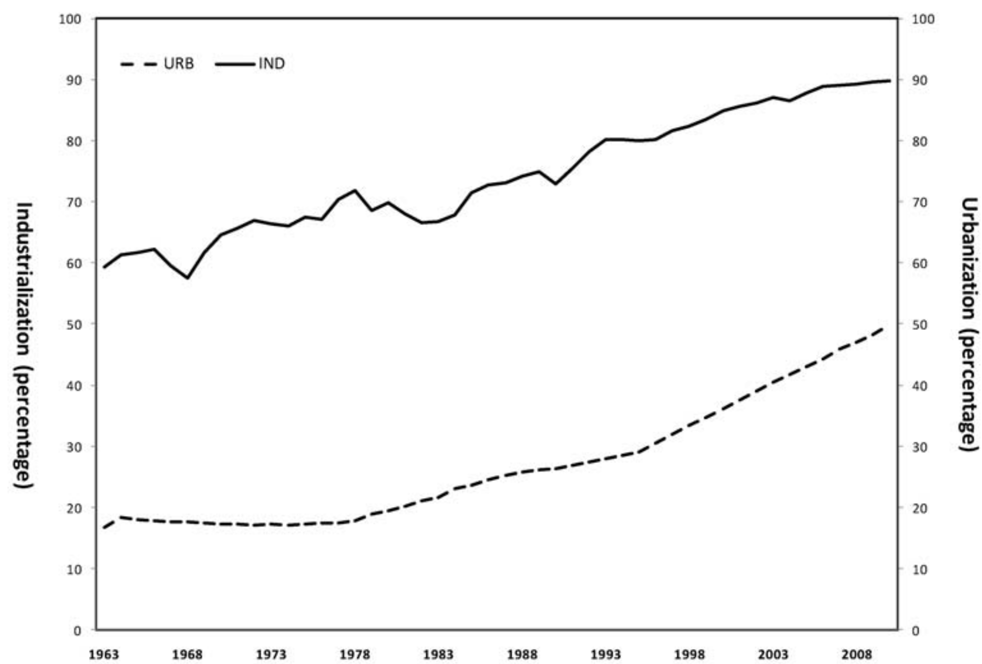
$$y_t = \mu^B + \beta^B t + \gamma^B DT_t^*(\lambda) + \alpha^B y_{t-1} + \sum_{j=1}^{k} c_j^B \Delta y_{t-j} + \varepsilon_t \tag{4}$$

3. Beside the test due to Zivot and Andrews, a similar test for unit root in case of endogenous structural break was proposed by Perron (1997).

Figure 1: Graphs of the Four Variables in the System



Panel A. GDP and EC



Panel B. IND and URB

Note: EC stands for energy consumption, GDP for gross domestic product, IND for level of industrialization defined broadly, URB for level of Urbanization.

Table 2: Result of ADF and PP Tests for Unit Root

	ADF		PP	
Series	Intercept	Intercept & trend	Intercept	Intercept & trend
Variables in levels				
EC	1.43	−0.47	3.70	1.06
GDP	4.32	3.73	22.57	10.76
IND	−0.42	−2.75	−0.18	−2.86
URB	3.98	−1.62	4.78	−0.08
Variables in first differences				
EC	−1.92	−2.66	−2.02	−2.85
GDP	1.46	−0.76	4.13	−0.08
IND	−6.00	−5.95	−6.30	−6.23
URB	−1.06	−6.99	−2.59	−6.68
Variables in second differences				
EC	−5.96	−5.91	−6.30	−6.32
GDP	−6.11	−6.94	−6.03	−7.76
IND	–	–	–	–
URB	−12.71	–	−14.43	–

Notes:
a. ADF and PP are unit root test developed by Dickey and Fuller, and Phillips and Perron respectively.
b. EC stands for energy consumption, GDP for gross domestic product, IND for level of industrialization defined broadly, URB for level of urbanization.
c. Critical values for the ADF test at 5% level without trend and with trend are -2.93 and -3.51, respectively. Critical values for the PP test at 5 % level without trend and with trend are -2.93 and – 3.51, respectively. For both tests, nonstationarity is rejected when calculated values are less than critical values.

$$y_t = \mu^C + \theta^C DU_t(\lambda) + \beta^C t + \gamma^C DT_t^*(\lambda) + \alpha^C y_{t-1} + \sum_{j=1}^{k} c_j^C \Delta y_{t-j} + \varepsilon_t \tag{5}$$

where, following Zivot and Andrews (1992) notation, we use superscript B and C to indicate the two alternative test hypotheses, and λ is the fraction indicating break point position, $DU_t(\lambda) = 1$ if $t > T\lambda$, 0 otherwise; $DT_t^*(\lambda) = t - T\lambda$ if $t > T\lambda$, 0 otherwise. y is the series being tested. Other variables, their transformations and parameters are as usually defined. As in the Dickey-Fuller type test, the key component of this test lies in the parameter α. When we reject the null of α being 1, we conclude that y_t is not a unit root process, instead, it is a trend stationary process with a structural break.

We apply the above ZA test to the four series respectively, with results shown in Table 3 indicating three significant break points. First, for the case of a break in slope, the test statistic on EC turns out to be -7.94. This value is lower than the critical value of 1% and 5% significance levels, suggesting that in 2002 there was a break point in EC. In the meantime, this result suggests that EC is not a unit root process. Instead, it is a stationary process around a broken deterministic trend. The test statistic for GDP turns out to be 1.27, greater than the critical value at 5% level. This result shows that there is no significant break point in GDP, and that we cannot reject the null hypothesis that GDP is nonstationary with unit root. Second, for the case of a break in both the slope and intercept, a significant break point in 2001 is identified for EC while no significant break

Table 3: Result of Zivot and Andrews Test for Unit Toot Subject to Structural Break

Variable	Breakpoint	Statistic	Critical value at 1%	Critical value at 5%
		Case 1: Break in slope only		
EC	2002*	−7.94	−4.93	−4.42
GDP	1999	1.27	−4.93	−4.42
IND	1984	−4.06	−4.93	−4.42
URB	1993	−3.66	−4.93	−4.42
		Case 2: Break in slope and intercept		
EC	2001*	−6.70	−5.57	−5.08
GDP	2000	1.68	−5.57	−5.08
IND	1981*	−5.76	−5.57	−5.08
URB	1996	−3.72	−5.57	−5.08

Notes:
a. EC stands for energy consumption, GDP for gross domestic product, IND for industrialization defined broadly, and URB for urbanization.
b. The null hypothesis of Zivot and Andrews test is that the original series is nonstationary with unit root; the alternative hypothesis is that the original series is stationary around a broken trend line.
c. For each variable, Zivot and Andrews (1992) test identifies a potential break point in Case 1 and 2 respectively that is most likely to reject the null hypothesis of nonstationarity. However, these potential break points are not confirmed as actual break points unless they are proven statistically significant. In our case, among the eight potential break points, three of them are statistically significant, as indicated by *.

point for GDP is obtained, as shown in the lower portion of Table 3. Third, for URB and IND, both are found to be unit root processes without any significant break point, except that IND, in the case of break in slope and intercept, rejects the unit root null, suggesting that it is trend-stationary process with break in 1981.

Summarizing, the ZA tests suggest one break point for IND and EC (we keep 2001 as the only break point for EC as 2002 is so close to 2001 and the case under which it is obtained is more restrictive) respectively. While the 1981 break point in IND seems obviously associated China's reform and opening-up policy that started in the late 1970s, the 2001 break point in EC appears more subtle. A few factors could be at play and we give two here. First, after a few years of troubled growth due to state-owned enterprise problems and the Asian financial crisis, the Chinese economy was back on a track of fast growth from 1999, and the growth was later enhanced by China's entry into World Trade Organization in 2001. Second, the Chinese economy actually transitioned into a phase of so-called 'heavy industrialization' shortly after 2000, resulting in an increase of energy intensity for the industrial sector. As a consequence of the change in both GDP and energy intensity, we observe an abruptly elevated energy consumption level since 2001.

Economic significance aside, the econometric significance of the identified break points, specifically the break point in EC, is also interesting. Nonstationarity, and further, the resulting cointegration for certain measures of energy consumption over certain sample periods, including electricity, coal and oil consumption, total energy consumption, and energy intensity are well established results in the literature (see for instance, Shiu and Lam 2004, Zou and Chau 2006, Yuan et al. 2007, Yuan et al. 2008, Liu 2009, Feng et al. 2009, and Bloch et al. 2012 among many others). Due to the extended view from ZA test, we can conclude that EC in this case is not nonstationary, but rather trend-stationary. As cointegration is meaningful only among nonstationary series with unit root, the trend-stationarity of EC therefore suggests that a long-run cointegration relationship between EC and GDP (and other variables too) is not justified in this case.

Therefore, for the system of four variables, we deviate from the analysis of long-run relationship, and instead examine the short-run interactions only. In what follows, we transform all four variables into their respective growth rates to achieve stationarity (test results available upon request), and study their short-run dynamic interaction in a model of ordinary VAR (instead of vector ECM). As a result of transforming the level variables into their growth rates, the effective sample in this study now starts from 1964, instead of 1963.

4. ECONOMETRIC METHODOLOGY

We use a VAR model to analyze the short-run dynamics of our multivariate system. In its standard (reduced) form, a VAR model with p lags can be expressed as

$$Y_t = A_0 + \sum_{l=1}^{p} A_l Y_{t-l} + e_t (t = 1, \ldots, T) \tag{6}$$

where Y_t is the $N \times 1$ ($N = 4$ in this case) vector containing the N variables studied in the problem. A_0 is an $N \times 1$ vector of constants and A_l an $N \times N$ matrix of coefficients, both to be estimated. e_t is the $N \times 1$ vector of residuals.

To find the causal interactions among variables for policy analysis, we have to uncover the structural form VAR that underlies the reduced form:

$$B_0 Y_t = \Gamma_0 + \sum_{l=1}^{p} \Gamma_l Y_{t-l} + \varepsilon_t (t = 1, \ldots, T) \tag{7}$$

where beside Γ_0 and Γ_l as the usual vectors of coefficient, B_0 is an $N \times N$ matrix defining the contemporaneous causal relationship among variables, and ε_t the $N \times 1$ vector of disturbances with each element orthogonal to each other. To recover such a structural form VAR from the fitted standard form VAR, a common approach is through the restriction of B_0, a process called identification in VAR.

4.1 Structural Identification Using Directed Acyclic Graphs (DAG)

When Sims (1980) first proposed VAR, identification was based on the Choleski decomposition method, i.e., by restricting a lower triangular B_0 matrix. Such a restriction implies that the variables in the VAR system follow a recursive causal order, which cannot be true of all cases. Some later proposed identification methods, particularly Structural VAR (SVAR, Bernanke 1986) and Generalized impulse response (GIRF) and generalized forecast error variance decomposition (GFEVD, Pesaran and Shin 1998) are more flexible in certain ways, but can suffer from either subjective restriction (for SVAR, Swanson and Granger 1997) or extreme assumption (for GIRF and GFEVD, Kim 2012). We adopt the data-driven identification approach introduced by Swanson and Granger (1997).[4] Using DAG method to define the contemporaneous relationship among variables, this approach reads contemporaneous causality (not limited to recursive structure) out of data

4. Compared to the method in Swanson and Granger (1997), the DAG method used in this paper and other DAG papers as we cite right below has been extended to suit more general types of causal flows among variables, instead of just linear chain of causality.

and uses such a causality to restrict matrix B_0. Essentially, this approach makes use of the flexible SVAR framework without depending on subjective economic priors.

A full description of the DAG methodology is beyond the scope of this paper. Interested readers can find details in Pearl (2000) and Spirtes et al. (2000), while more accessible introduction and applications are available in Demiralp and Hoover (2003), Bessler and Yang (2003), Park et al. (2006), Mjelde and Bessler (2009), and Yang and Zhou (2013). Briefly, with its origin in computer science and artificial intelligence, DAG provides a way to read a causal pattern out of observed data. Represented by a graph, the causal pattern consists of vertices (standing for the variables studied in a particular problem) and edges connecting the vertices. Such a pattern can represent different types of causal flows by different types of edges: (1) directed edge ($\rightarrow$), (2) bi-directed edge ($\leftarrow\rightarrow$), (3) undirected edge (−−), and (4) no edge, to indicate unidirectional causality, bidirectional causality, undirected correlation, and lack of correlation respectively. These edges are used to define which elements of the B_0 matrix need to be parameterized.

It is worth noting that just as it is true of other conventional statistical methods, DAG can also err in its inference. In our implementation of the DAG-VAR approach based on Eviews and TETRAD (Scheins et al., 1994), we use more than one algorithm of DAG, GES (Chickering, 2003) and PC algorithm (Spirtes et al., 2000), to ensure the results are as robust as possible. Specifically, we choose GES as the main algorithm as it gives no undirected edges in almost all cases of our analysis. In addition, following Spirtes et al. (2000) and Demiralp and Hoover (2003), we use PC algorithm under alternative levels of significance for causal pattern. We then match the most consistent pattern from PC algorithm to that of GES. It turns out that all directed edges of GES are confirmed by the directed ones from PC. We then use the confirmed patterns for VAR identification.

4.2 The Framework of Rolling Windows

To reveal possible changes in system dynamics across time, in addition to results for the whole sample, we embed the DAG-based VAR within a rolling window framework. Rolling window estimation as a general approach to deal with structural instability has been used in a number of studies (e.g., Thoma 1994, Swanson 1998, Psaradakis et al. 2005, Balcilar et al. 2010). In this study, we start with a subsample ranging from t_0 to t_{0+h}, i.e., a sample of h years which we call window 1. For this window, a reduced form VAR is estimated, then structural identification done using DAG, and the innovation accounting analysis carried out to find the interactions among variables. Next, at some defined interval s, we move the window of span h to cover the next subsample period (from t_{0+s} to t_{0+s+h}), then repeat the VAR estimation, structural identification and innovation accounting. This process is continued until the end of the full sample is reached. By this rolling window approach, the changing nature of the relationship among the variables can be revealed via a conventional VAR framework.

We first estimate the system for the full sample to provide a benchmark assessment of the system dynamics, including the lag structure. For the full sample, the optimal lag length of the system is determined first based on Schwarz and Akaike information criterion (SIC/AIC), with both criteria achieving the minimum value at the lag order of two.[5] This lag order is applied to each of the rolling windows. Given this two lag structure, our sample now effectively starts at 1966, the first year of the 3rd "five-year plan".[6] In determining the rolling window length h, our basic con-

5. A Lagrange multiplier test for serial correlation was conducted on the unrestricted VAR with two lags. The test statistic is 19.71. Under a degree of freedom of 16 under Chi-square distribution, this statistic translates into a probability value of 0.23, indicating no remaining serial correlation.

6. The "five-year plan" system in China was initiated shortly after the foundation of the People's Republic of China in 1949. As a comprehensive planning system for China's economic and social development, the five-year plan is principally

Table 4: Definition of Five Windows (Subsample Periods) for Rolling-window Analysis

	Start	End	Duration
Window 1	1966	1990	25
Window 2	1971	1995	25
Window 3	1976	2000	25
Window 4	1981	2005	25
Window 5	1986	2010	25

sideration is to balance degree of freedom requirement (favoring a longer window) against the effect that too long a window may make it more difficult to observe the changing structure of the system over time (favoring a shorter window). Based on this consideration and preliminary estimates, a span of 25 years is chosen to be the length *h*, corresponding to five "five-year plan" periods. In determining the interval *s*, for tractability and ease of exposition, instead of moving the windows at interval of one year, we move the windows over five year intervals. The joint determination of *h* and *s* gives us five rolling windows with each spanning 25 years, as summarized in Table 4.

5. RESULTS AND DISCUSSIONS

Based on the DAG VAR model in a rolling-window framework, we analyze the interrelationships of the four variables in the system. There are two key aspects to our analysis. First, given the estimated unrestricted VAR system, the contemporaneous causal structure of the VAR system is identified using the DAG approach. Second, the resulting innovation accounting results, particularly forecast error variance decompositions (FEVD),[7] are presented to illustrate the causal relationships among the variables. This section proceeds by first considering these two aspects of the results for the full sample in Subsection 5.1 and 5.2 before presenting the results for five subsamples in Subsection 5.3.

5.1 Contemporaneous Causality for the Full Sample

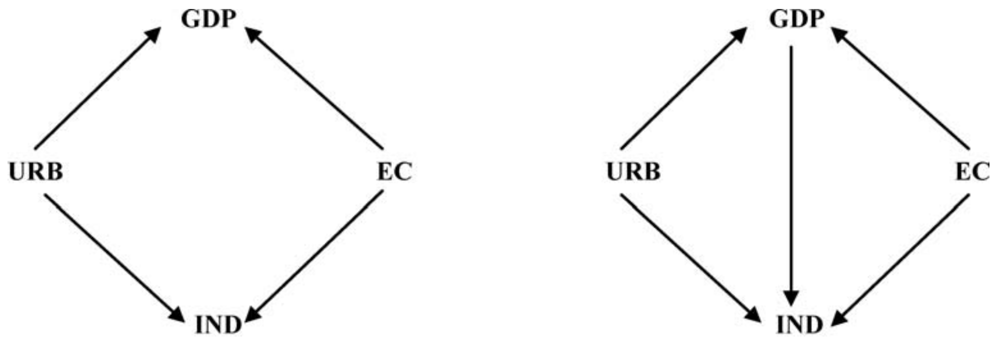
As discussed in Section 4, a lag of 2 is chosen for the system estimation over the full sample. Based on the correlation matrix of residuals estimated from such a unrestricted VAR model, we use the GES algorithm (Chickering, 2003) of DAG to find the pattern of contemporaneous causality, which in turn, identifies the VAR in structural form. The resulting pattern of contemporaneous causality is shown in Figure 2.

As can be seen, there are a total of four directed edges (causal flows) among the four variables: the two causal flows from EC to GDP and IND, and the other two from URB to GDP and IND. This means that contemporaneously, EC causes both GDP and IND, and given that no

made and implemented by the central government, and has always been fundamental in drawing an overall picture for China's development over a five-year cycle. Although this system was initiated during the planned economy regime and was most influential back then, it is still very influential today even though the Chinese economy is much more market-oriented.

7. In addition to FEVD, impulse response function (IRF) is another type of innovation accounting analysis. While FEVD and IRF are both based on the same structural model and convey qualitatively the same information regarding causal relationship among variables, FEVD measures variables response clearly on the same relative scale (all in percentages), which is more suitable for over time comparison in this case.

Figure 2: DAG Contemporaneous Causal Pattern for the Full Sample



Panel A. Based on the broad IND

Panel B. Based on the narrow IND

Notes:
a. EC stands for energy consumption, GDP for gross domestic product, IND for level of industrialization, URB for level of Urbanization.
b. Panel A and B differ in that Panel A is based on the broad IND defined over nonagricultural sectors, while Panel B is based on the narrow IND defined over the secondary industry only.

variables cause EC, it is suggested that EC is the exogenous variable when compared to GDP and IND. Similar to EC, URB is exogenous contemporaneously, given that it causes both GDP and IND while caused by none. The results regarding EC therefore suggest that aside from the well documented effect of energy consumption on the level of economic growth (both in short-run and long-run), energy consumption also affects the structure of the economy (the degree of industrialization) in contemporaneous dimension. Note that while contemporaneous means instantaneous, the degree of instantaneity is up to the frequency of data used. Given the data being annual, contemporaneous causality means causality that happens within one year. Later, FEVD results will reveal causality in longer horizon (still short-run causality when compared to causality within a cointegration relationship).

For our four-variable system, the pattern in Figure 2 actually supplies eight zero restrictions (two more than the required six for just identification), resulting in an overidentified system. Given such a contemporaneous causal pattern, the structural VAR can now be identified by restricting the B_0 matrix in equation (7).

5.2 FEVD Results for the Full Sample

Based on the structurally identified VAR, the FEVD results are obtained for the full sample and given in Table 5 covering a five-year forecast horizon. This horizon is chosen as the variables' responses to shocks in the results are generally stable by the 5th year. For each variable, the result is shown by one of the four panels in Table 5. For each panel in the table, there are 6 rows showing the variance decomposition of that variable from time zero (contemporaneous or current period) to five years ahead. The first panel shows how the variations of GDP depend on itself and the other three variables in the system. At time zero, 38% of GDP growth is due to itself while EC explains a further 56%, and URB a much smaller 6%. Over the 5 year horizon, the percentage of EC drops slightly to 52% while that of URB rises dramatically to 14%. The contribution of IND is very limited, no more than 1% over the whole horizon.

Table 5: FEVD Result for the Full Sample

GDP	GDP	EC	IND	URB
0	38.3	56.0	0.0	5.7
1	34.2	55.9	0.1	9.7
2	34.8	52.3	0.1	12.8
3	33.5	53.0	0.4	13.1
4	33.4	52.6	0.5	13.5
5	33.9	51.9	0.5	13.7
EC	**GDP**	**EC**	**IND**	**URB**
0	0.0	100.0	0.0	0.0
1	13.0	86.2	0.7	0.0
2	30.2	68.6	0.8	0.4
3	31.0	65.3	1.8	1.9
4	30.2	64.2	2.1	3.6
5	31.4	62.4	2.0	4.2
IND	**GDP**	**EC**	**IND**	**URB**
0	18.1	26.4	49.4	6.1
1	19.4	27.6	47.0	6.0
2	25.4	27.1	42.1	5.5
3	25.5	28.2	40.9	5.4
4	25.8	28.0	40.6	5.6
5	26.3	28.0	40.2	5.6
URB	**GDP**	**EC**	**IND**	**URB**
0	0.0	0.0	0.0	100.0
1	2.8	0.4	0.8	95.9
2	2.9	1.1	0.8	95.2
3	2.8	1.1	0.7	95.3
4	2.7	1.0	0.7	95.6
5	2.6	1.0	0.6	95.8

Note: EC stands for energy consumption, GDP for gross domestic product, IND for level of industrialization defined broadly, URB for level of urbanization.

The second panel of Table 5 shows how EC variation is explained by itself and the other three variables. At time zero, consistent with the contemporaneous causality suggested by the DAG analysis (in Figure 2), EC is exogenous, explaining 100% of its own variation. As time goes on, EC is explained increasingly by GDP up to 31%. Compared to GDP, the effects of IND and URB on EC are much smaller. IND explains as much as about 2% of EC over the horizon, while the effect of URB is roughly double that of IND at about 4%. Comparing the results in the first two panels of the table, it is clear that between GDP and EC, there exists a two-way causality in the short-run, with each variable explaining a significant portion of the other over the five year horizon. In the meantime, EC appears to be the relatively more exogenous variable, as it explains greater portion of its own variance over the five-year horizon than GDP does.

The third panel of Table 5 shows the results for IND. Briefly, other than the effect of IND on itself, EC explains the greatest part of the IND variation (between 26 and 28% over the horizon), followed closely by GDP (up to 26%). The effect of EC on IND implies that energy consumption is important to the process of industrialization. As to the relationship between IND and GDP, recalling that IND explains less 1% of GDP in the first panel, it can be inferred that GDP is more exogenous than IND, i.e., the change of economic scale tends to cause the change of economic structure, but not the reverse. Finally, other than EC and GDP, URB has a much smaller effect, explaining roughly 6% of the IND variance.

The fourth panel of Table 5 reports the results for URB. Over the 5 year horizon, URB consistently explains over 95% of its own variation, leaving very limited room for the other variables, particularly, no more than 3% for GDP, and negligible percentages for EC and IND. One implication of these results is that urbanization in China, consisting mainly of the inflow of a large amount of the rural population into cities and towns (Zhang and Song, 2003), is not driven directly by the regional/macroeconomic development, such as the immediate need for labor in manufacturing and service sectors; Instead, urbanization may have been driven by the prospect of better life in the future. However, this further implication can only be conjectured with our available data.

In summary, the full sample FEVD results demonstrate, among other things, the two-way causal relationship between energy consumption and economic growth, similar for instance to the finding in Akkemik and Goksal (2012). Meanwhile, representing another facet of an integrated relationship, the relative exogeneity of EC over GDP is also shown, echoing other studies that report the unidirectional causality from energy to growth. Further, the FEVD results demonstrate that IND and URB, though important components of the VAR system, have only limited effects upon EC and GDP.

5.3 FEVD Results for Five Subsamples

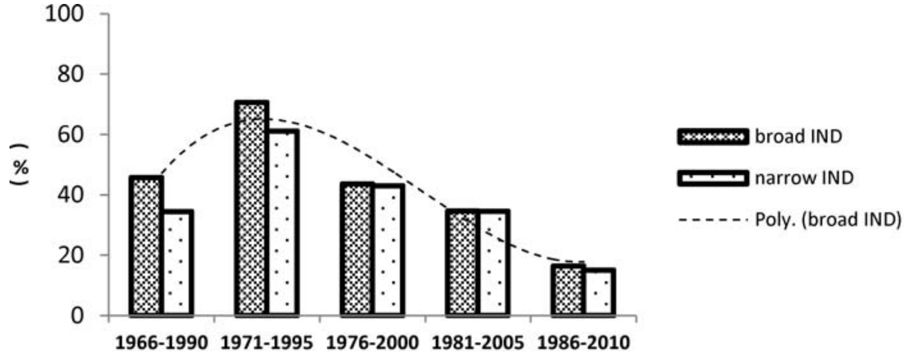
As discussed in the methodology section, we re-estimate the DAG VAR for each of the five windows and the resulting FEVD results across windows are summarized into a unified framework, as given in Figures 3, 4, and 5 respectively for a selection of variable relationships. For example, Panel A of Figure 3 shows the effect of EC on GDP, where each of the five bars represents the percentage of GDP variation due to EC at the 3rd year of the five year horizon for each of the five rolling windows respectively.[8] Other panels of the three figures are defined similarly.

Starting with Panel A of Figure 3, the percentage of GDP variation due to EC demonstrates a systematic change across the five windows. With the exception of an increase from window 1 to window 2, the percentage drops steadily over time to just 20% by window 5. Panel B shows the effect of IND on GDP and that the percentage of GDP variation due to IND is no more than 5% for most windows, with a downward trend. In contrast, URB (in panel C) seems to play a bigger role in GDP growth, especially during window 5 (covering the period 1986 to 2010). However, there is no monotonic trend in this relationship. In comparison to the full sample result, the rolling-window result reaffirms the effect of EC on GDP, and importantly reveals that the strength of this effect has been decreasing over time.

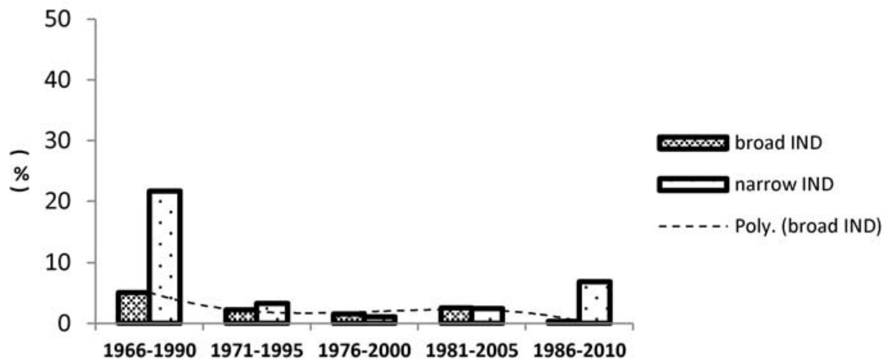
Figure 4 reports how the effects of GDP, IND and URB on EC change over the five windows. For window 1 of panel A in Figure 4, 30% of EC variation is due to GDP, and the percentage drops systematically to below 10% by the 5th window. Panel B reveals the effect of IND on EC to be overall small and stable across the windows, except that for window 4 (1981–2005) IND once had a relatively larger effect. In Panel C, except for an increase from window 1 to window 2 (1971–1995), we see an overall decrease in the effect of URB on EC.

8. The 3rd year result is chosen because although the FEVD results are time varying over the horizon, their relative variations are fairly stable and can be well represented by the 3rd year value, hence the results for the other years offer little extra information.

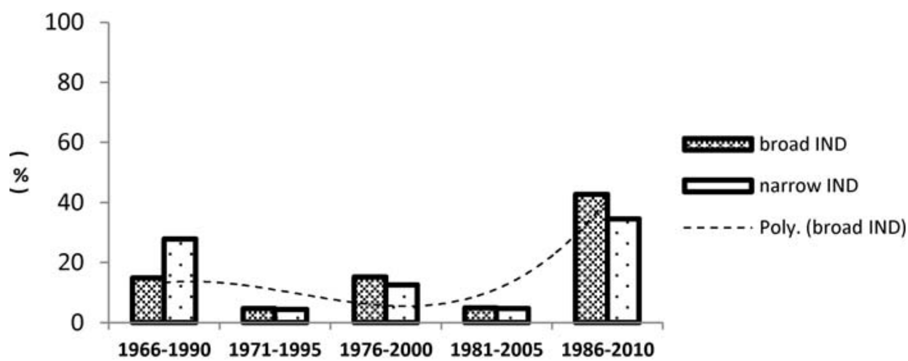
Figure 3: The Rolling-window FEVD Results for GDP



Panel A. GDP due to EC



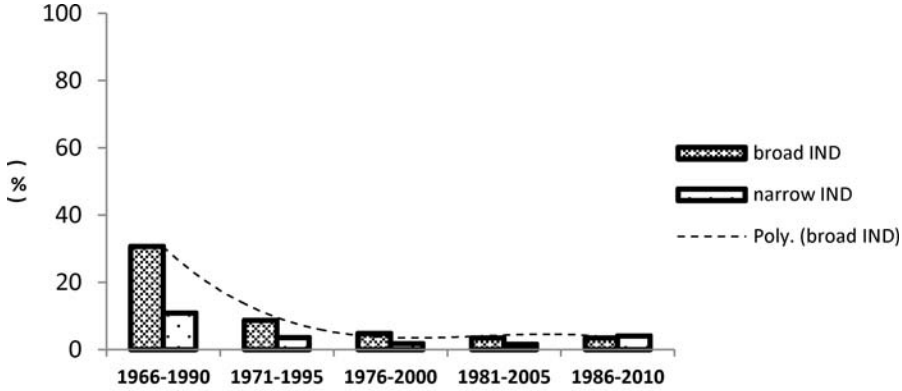
Panel B. GDP due to IND



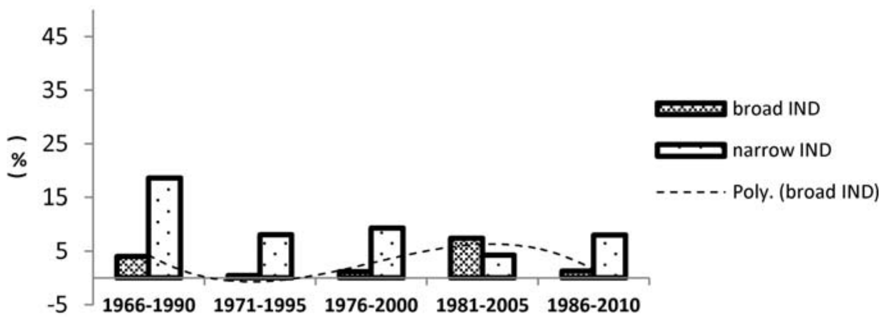
Panel C. GDP due to URB

Notes:
a. Bars in the figures stand for the corresponding FEVD results. The dashed lines are fit lines of cubic polynomial.
b. EC stands for energy consumption, GDP for gross domestic product, URB for level of urbanization, broad IND for level of industrialization defined broadly over nonagricultural sectors, and narrow IND for level of industrialization defined narrowly over the secondary industry.

Figure 4: The Rolling-window FEVD Results for EC



Panel A. EC due to GDP

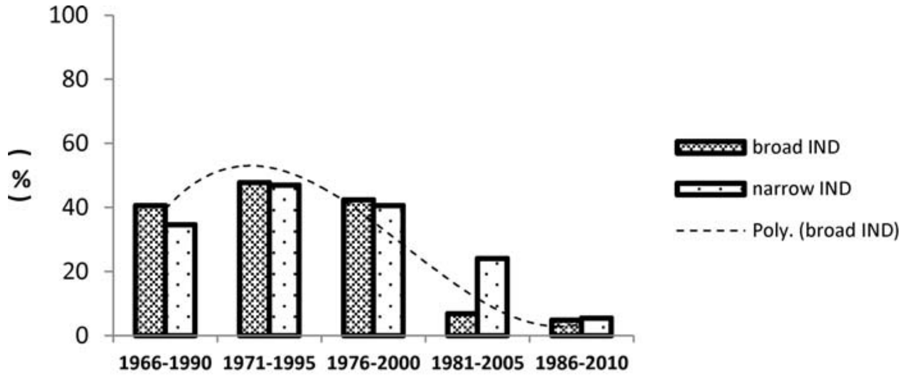


Panel B. EC due to IND

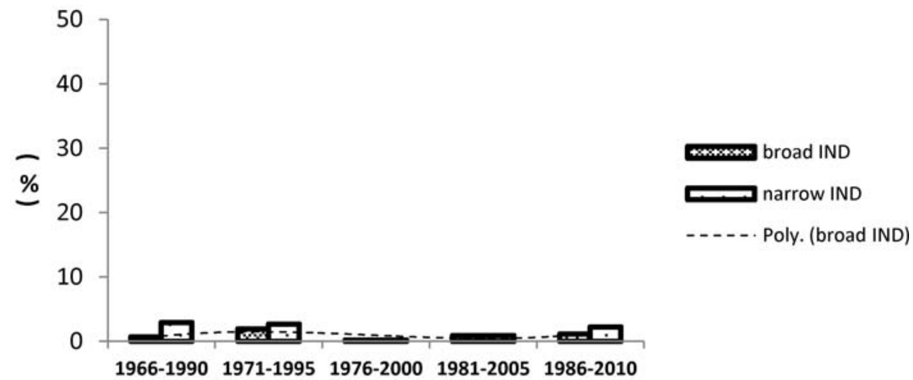
Panel C. EC due to URB

Notes:
a. Bars in the figures stand for the corresponding FEVD results. The dashed lines are fit lines of cubic polynomial.
b. EC stands for energy consumption, GDP for gross domestic product, URB for level of urbanization, broad IND for level of industrialization defined broadly over nonagricultural sectors, and narrow IND for level of industrialization defined narrowly over the secondary industry.

Figure 5: The Rolling-window FEVD Results for IND and URB



Panel A. IND due to EC



Panel B. URB due to EC

Notes:
a. Bars in the figures stand for the corresponding FEVD results. The dashed lines are fit lines of cubic polynomial.
b. EC stands for energy consumption, GDP for gross domestic product, URB for level of urbanization, broad IND for level of industrialization defined broadly over nonagricultural sectors, and narrow IND for level of industrialization defined narrowly over the secondary industry.

Figure 5 reports the percentages of the variance in IND and URB due to EC as an evaluation of energy consumption's effects on industrialization and urbanization. Panel A of this figure shows the percentage of the IND variance due to EC. Across windows, the effect of EC on IND variance experiences a significant drop since window 3, suggesting that the industrialization process has become less energy-dependent. In comparison, as shown in Panel B, EC has little impact upon URB across windows, confirming the full sample result that urbanization is more exogenous than the other variables of the system.

5.4 Discussion: Interpretation of the Main Results

If we compare the rolling-window result to that of the full sample, we can see that overall the two sets of results are similar to each other. Principally, regarding the energy consumption and

GDP relationship, the full sample result suggested that there exists mutual causality between the two variables, and that energy consumption is relatively more influential when compared to GDP. The rolling-window result broadly confirms the full sample result. In our view, the rationale for the two-way causality is as follows. On one hand, there is the causality from energy to growth given that energy is one important factor for an economy. On the other hand, energy consumption is not a purely exogenous variable in relation to output. Generally speaking, how much energy to consume depends on the demand from the economy output as determined by multiple factors not limited to energy availability. When the economy is expanding, the energy sector is driven to supply more energy to meet the demand. In contrast, when the economy slows down, the energy sector will be under pressure to reduce its supply in response to less demand. Recently, the experience of the coal industry in China exemplifies what a slower Chinese economy can do to its energy sector to adjust its supply (Financial Times, 2012; Xinhua News Agency, 2012).

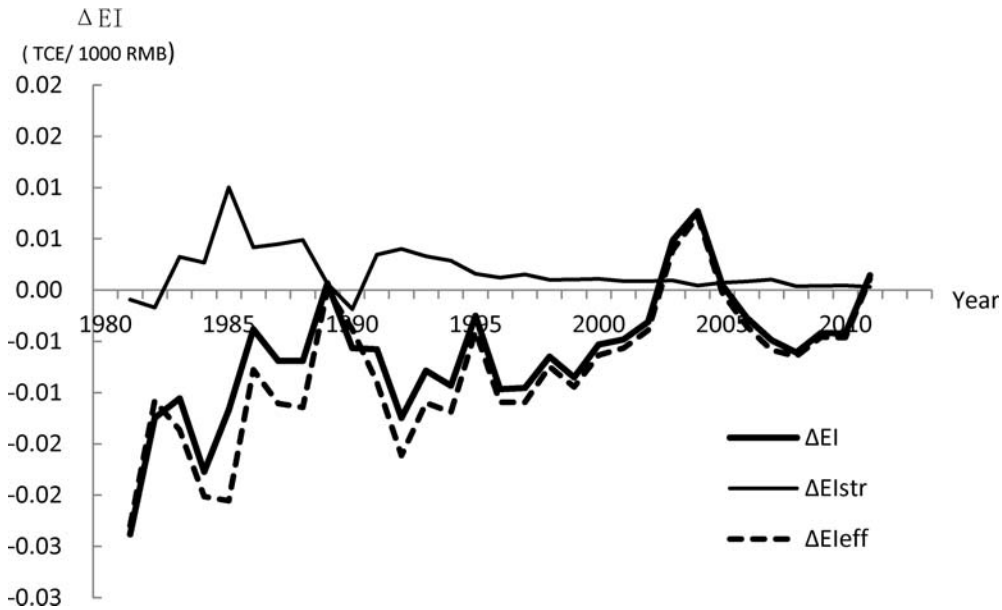
Further, the rolling-window results seem to offer a much richer and arguably more precise description of system dynamics that is not available from the full sample result. Specifically, over time the two-way causality between energy consumption and GDP has been decreasing in strength. The decreasing effect mainly occurs during windows 3 through 5, i.e., the period featuring the dramatic drop of energy intensity in China. We argue that this decreasing effect of energy on GDP can be interpreted as a decreasing reliance of GDP on energy, as the Chinese economy becomes more dependent on other factor inputs, especially technology or labor, as for example suggested by Su et al. (2012). Since the causality from energy to growth arises from energy being an important input for the economy, less reliance of output on energy naturally translates into a reduced causal effect of energy on output. Due to the same issue of energy intensity drop, the same degree of economic growth now means less increase of demand on energy, implying a decreasing causal effect of GDP on energy consumption.

Regarding the effects of industrialization and urbanization, while the full sample result shows both to have limited effects on EC and GDP, the rolling-window result shows that the effects of the two structure variables are larger in certain stages than in others, particularly for urbanization. The overall limited effect of IND on EC can be traced to the relatively low energy intensity of the agricultural sector (or vice versa, the relatively much higher energy intensity of the nonagricultural sectors). According to data from various issues of the China Energy Statistical Yearbook, for most of the years, the energy intensity of the agricultural sector has been below one-fifth of that of all nonagricultural sectors combined. This much lower energy intensity means that the changing share of the agricultural sector in GDP has a much reduced effect on energy consumption. This is true recently in 2010 when the agricultural sector's share in GDP is 10 percent with its energy consumption share being only 2 percent, and this was also true back in 1985 when its GDP share was 28.4 percent and its energy consumption share 5 percent. Hence the energy consumption of this sector has only marginal impact, irrespective of its output share in the economy. A similar explanation applies to the effect of urbanization on energy consumption. In a way, the results on IND and URB's limited effects complement the finding in Kahrl et al. (2013) which finds that the vast majority of energy consumption growth in China since 2002 is due to GDP growth, not structural change. Our findings here indicate that this is actually true not just for the post-2002 years, it has been the case for a much longer period.

5.5 Extension: From GDP-EC Causality to the Cause of Energy Intensity Change

The limited effect of IND on EC has its implications beyond the energy-growth causality. The recent decades have witnessed a continuous drop of China's energy intensity (EI), the amount

Figure 6: Energy Intensity Change and the Contributions of Structure and Efficiency



Note:
ΔEI, ΔEI_{eff}, ΔEI_{str} stand for the energy intensity change, the part of energy intensity change due to structure, and the part of energy intensity change due to efficiency, respectively. TCE stands for ton of coal equivalent.

of energy consumed per unit of GDP. Despite a number of studies into this issue, conflicting findings remain as to what has caused such a drop of energy intensity. The literature is divided between the studies (e.g., Huang, 1993b; Ma and Stern, 2008; Zhang, 2003; Wu, 2012) assigning sectoral energy intensity (efficiency) as the main reason, and the studies (e.g., Fisher-Vanden et al., 2004; Zhao et al., 2010; Yu, 2012) showing that structural change does matter.

EI is not explicitly modeled in this study, but given its definition, EI is affected to the same degree (in percentage) as EC by a third variable if GDP is a constant. And indeed, GDP is held constant when FEVD measures the effect of IND on EC (given shocks being orthogonal in structurally identified VAR). The limited effect of IND on EC then tends to suggest the same degree of limited effect on EI. One step further, as EI can be decomposed to depend on either structural effect or efficiency effect, then, the limited effect of IND on energy intensity goes without saying that the efficiency effect will explain the remaining larger share for China's energy intensity drop over the decades.

As a check of the above reasoning,[9] we use the popular index decomposition approach (IDA) to offer a direct evaluation for the relative contributions of structure change and efficiency change. Using IDA, we decompose conceptually the change of EI into the part due to the change of structure (captured by IND alone), and the part due to the changes of energy intensity in two sectors (captured by I1 and I2 for agriculture and nonagriculture sector) with details given in Appendix. We then apply this decomposition to the Chinese data between 1980 and 2010. As shown in Figure 6, the change of energy intensity is mostly due to the effect of sectoral energy intensity

9. We thank one anonymous referee for pointing out the need for more substantive examination of this issue.

change, the effect of structural change is quite limited. This result then, from another perspective, confirms the foregoing reasoning extended from FEVD based result. Overall, the above results, FEVD-based inference and IDA result, echoes the aforementioned papers which assign a bigger role to efficiency, and in particular Feng et al. (2009) who in a time series setting finds that changing economic structure (defined as the share of the tertiary industry in GDP) had limited effect on energy intensity.

The above said, it is worth noting that due to the issue of aggregation, the implication of economic structure depends on the level at which it is defined. The variable IND used here is defined at a very aggregate level, and cannot be generalized to more disaggregated levels without qualification. In addition, as shown in Figure 6, there is an abrupt change of pattern between 2003 and 2006. We discuss the two issues in the next two subsections.

5.6 Alternative View: When Industrialization Means Only the Secondary Industry[10]

We have so far based our analysis on the broad definition of industrialization (IND covering both the secondary and tertiary industry). While economic structures defined at different levels have their respective policy implications and the broad definition is important as it captures a baseline feature of the Chinese economy, it is also true that the broad definition can conceal the likely effects of structure at more disaggregated level (e.g., Ang, 1995; Su et al., 2010). For robustness of results and a finer view into the issue, we now break down the nonagricultural sector and use only the share of the secondary industry in GDP as the measure for IND. With the narrow IND, we then repeat the whole set of DAG-VAR analysis, including full sample contemporaneous causality, full sample FEVD, and rolling-window FEVD.

Shown in Panel B of Figure 2 is the contemporaneous causal pattern based on full sample. Compared to the pattern in Panel A, we now see the causal flow from GDP to IND. Other than this, all other causal flows hold as before.

The full sample FEVD results are very close to those in Table 5 and thus are not presented for brevity. Instead, for a finer comparison, the rolling-window FEVD results are presented along with those based on the broad IND, as in Figures 3, 4, and 5. Among the eight pairs of relationships shown there, only two pairs show meaningful deviation from the set based on the broad IND. Specifically, in Panel B of Figure 3, IND shows greater effect on GDP during window 1 and window 5; Further, in Panel B of Figure 4, IND shows greater effect on EC over all five windows. However, even for the above two cases, the percentage of GDP and EC variance due to IND remain low, barely over 20 percent at the maximum point. Other than the two, the other six pairs of relationships (including the IND-EC pair in Panel A of Figure 5) are similar to their counterparts under the broad IND.

In summary, under the narrow definition, IND shows somewhat greater effect on GDP, and especially EC. The greater effect may have been caused by disaggregation. Aggregation leads to the structure effect at more disaggregated levels being counted as efficiency effect. Disaggregation therefore reveals the concealed effect of structure. Overall, the baseline results hold for the alternative definition of IND.

5.7 Further Issue: The Change of Econometric Structure over Very Short Horizon[11]

We have adopted the rolling-window approach to reveal change of econometric structure not available from existing studies, however, question remains as to whether the issue of structural

10. We thank two anonymous referees for pointing out the need for a more disaggregated measure of IND.
11. We thank one anonymous referee for pointing out the issue of within-window structural change.

change has been fully addressed. The answer seems to be a "No". Of particular attention is the potential structural change around 2002. ZA test result earlier suggests that there is a point of break in EC series at 2001/2002. This break in single series also indicates potential change in the system dynamics. Unfortunately, unlike the breakpoint in IND at 1981, the 2002 breakpoint occurs at the middle of our last window and cannot be captured effectively by the rolling-window approach.

The economic intuition behind this break seems reasonably easy to obtain. A graphic and numerical check of data show that between 1986 and 2010, EC is the only variable showing significant change of growth rates before and after the breakpoint (from 3.2% to 8.8%). At a closer look, the rate of growth is especially high for the years from 2003 to 2006, and has dropped back to normal since then. A number of studies have addressed this fluctuation. Among others, Liao et al. (2007) documented the abnormal rise of energy intensity and attributed it to the expansion of more energy-intensive subsectors using IDA method (Tornqvist and Sato-Vartia index method, to be specific).

Further claim on causality as the one from innovation accounting of VAR, however, is hard to do. As explained in Section 4, the inherent degree of freedom issue in VAR and the low frequency of data mean that it is not practical for the rolling-window approach (and other time series approaches as well, e.g., Primiceri 2005) to estimate a model over a horizon of less than 10 periods. As one solution, the effort to establish the causality over such a horizon, when needed, may resort to variables in higher frequency. That analysis would require a different system. We leave this issue to further research.

6. CONCLUSION

A number of studies have addressed the relationship between China's energy consumption and economic growth. Compared to existing studies, our approach to this issue is distinguished mainly in the following two ways. First, we examine, for the first time, the time-varying relationship between energy consumption and economic growth for China in a VAR system. We do so by first testing for structural break of individual series, and further by studying the change of system dynamics using a rolling-window VAR approach. Second, by introducing two structural variables, industrialization and urbanization, we study China's energy-growth relationship in the context of its continued industrialization and urbanization between 1963 and 2010. The findings thus shed light on, at a very aggregate level, how the changes of China's fundamental structural variables interact with energy consumption and economic growth.

The results, while confirming some findings in the literature, additionally reveal several points not available from existing studies. First, in the time-varying perspective, we are able to show that given energy consumption being trend-stationary, the cointegration and error correction processes commonly followed in the related literature are not suitable in this case. Instead, there exist non-constant interactions among the four variables. Specifically, the two-way causality between energy consumption and GDP has been decreasing in strength over time. Second, the structural (relative) dimensions of industrialization and urbanization, especially for the former, have overall limited effects on energy consumption. Comparatively, the scale of the economy is a far more influential force in determining energy consumption. Third, extended from the limited effect of industrialization on energy consumption, we show that the drop in China's energy intensity has come not from the structural shift between its agricultural and industrial sector, but from efficiency gained within the sectors.

Suggesting hope and direction for the future, the three findings have important implications for China's energy and growth policy. First, the lack of a long-run relationship between energy consumption and GDP (and other variables in the system) might be considered as a reassuring finding. It indicates that it is possible for China to sustain economic growth and reduce energy consumption at the same time. Second, the relatively limited effects of industrialization and urbanization on energy consumption, plus the reduced potential for either process after decades of development, suggest that even if China's industrialization and urbanization continue into the future, further reductions of energy intensity for China should be possible, and fostering further energy efficiency gains within the sectors of the economy should be the primary route.

APPENDIX

We show below step-by-step for a context of industrialization, how the change of overall energy intensity can be decomposed into the part due to structural change, and the part due to efficiency change. Based on index decomposition approach (IDA), the energy intensity of a two-sector economy can be decomposed as:

$$EI^t = S_1^t I_1^t + S_2^t I_2^t \tag{A.1}$$

where S_1^t, S_2^t stand for the shares of agricultural and industrial sector in GDP, and EI^t, I_1^t, I_2^t stand for the energy intensity for the economy and two sectors respectively. Given that S_1^t and S_2^t sum up to one, the above decomposition can be further shown as

$$EI^t = (1 - S_2^t) \cdot I_1^t + S_2^t I_2^t \tag{A.2}$$

That is, the structural change (industrialization) is captured by S_2^t alone while the efficiency change has to be captured by I_1^t and I_2^t together. Based on this setup, the change of energy intensity over time (e.g., one year)$\Delta EI = EI^t - EI^0$ (similar definitions apply to the changes of I_1^t, I_2^t, and S_2^t) can be decomposed as follows

$$\begin{aligned} \Delta EI^t &= [(1 - S_2^t) \cdot I_1^t + S_2^t \cdot I_2^t] - [(1 - S_2^0) \cdot I_1^0 + S_2^0 \cdot I_2^0] \qquad \text{(A.3)} \\ &= I_1^t - I_1^0 - S_2^t \cdot I_1^t + S_2^0 \cdot I_1^0 + S_2^t \cdot I_2^t - S_2^0 \cdot I_2^0 \\ &= \Delta I_1 - (S_2^0 + \Delta S_2) \cdot (I_1^0 + \Delta I_1) + S_2^0 \cdot I_1^0 + (S_2^0 + \Delta S_2) \cdot (I_2^0 + \Delta I_2) - S_2^0 \cdot I_2^0 \\ &= \Delta I_1 + S_2^0 \cdot (\Delta I_2 - \Delta I_1) + \Delta S_2 \cdot (I_2^0 - I_1^0) + \Delta S_2 \cdot (\Delta I_2 - \Delta I_1) \end{aligned}$$

Further, the above terms can be grouped into three terms as below

$$\Delta EI_{eff} = \Delta I_1 + S_2^0 \cdot (\Delta I_2 - \Delta I_1) = (1 - S_2^0) \cdot \Delta I_1 + S_2^0 \cdot \Delta I_2 \tag{A.4}$$

$$\Delta EI_{str} = \Delta S_2 \cdot (I_2^0 - I_1^0) \tag{A.5}$$

$$\Delta EI_{res} = \Delta S_2 \cdot (\Delta I_2 - \Delta I_1) \tag{A.6}$$

where ΔEI_{eff}, ΔEI_{str}, ΔEI_{res} stand for the contribution of efficiency change, structural change, and residual respectively. ΔEI_{eff} and ΔEI_{str} are defined so as they are due to respectively the change in efficiency (ΔI_1 and ΔI_2) and the change in structure (ΔS_2).

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