Historical simulations with a dynamic CGE model: results for an emerging economy

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Abstract

Policy analysis with a dynamic CGE model requires a baseline solution that is a plausible forecast of the whole set of model's variables. An important issue in the development of the baseline forecast is to account for structural change. This is aided by the technique of historical simulations which helps identify the characteristics of structural change in the past.

In this study we present our experiences with historical simulations using a recursive-dynamic CGE model for Poland. In historical simulations with a CGE model the observable macro and industry variables are exogenised, while endogenising technology and taste parameters. This allows to uncover the movements of the latter, which we do year-by-year.

Preliminary results show a relatively large variation of technology, taste and related parameters required to fit the data. The irregular component of this variation significantly impedes short-run CGE forecasting.

Introduction

Generating forecasts of the economy's structure can be seen as an important component of CGE-based policy analysis. As noted by Dixon and Rimmer (2002, p. 4) the results of CGE "what-if" analyses may significantly depend on the shape of baseline forecast. This might particularly be the issue with emerging economies, undergoing substantial structural changes, such as Poland.

Developing the baseline forecast involves projection of the full input-output (or social accounting) matrix, which serves as a benchmark database for model calibration. In such a process the available partial information – typically including macro data or forecasts – is incorporated to produce projections for detailed industry/commodity level variables. A potentially important aid in the development of the basecase forecast comes from the so called historical simulations, which help uncover the components of the structural change, i.e. – broadly – changes in technology and tastes.

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In this paper we empirically examine the ability of a CGE model to produce reliable forecasts of industry outputs and prices – with and without the supply of historical simulations' results. We generally follow the idea presented by Dixon and Rimmer (2010; see also Giesecke, 2008). However, our historical and forecast simulations are carried out in a year-to-year setting which, as demonstrated further, also allows us to address the problem of model's validation in a novel way.

Our model is based on Mini-USAGE – a simplified version of USAGE, the MONASH-style recursive dynamic CGE model of the U.S. economy (Dixon and Rimmer 2005; 2002). The benchmark input-output data concerns the year 2000. In the exercise we also use various annual industry/commodity-level time series for the years 2001-2005, as well as macro data for that period. We distinguish 18 industries/commodities in the model, which represents aggregate version of the available input-output data. The forecast and historical mode of the model's operation – explained in the following sections – are facilitated by appropriate closures, defining the split between endogenous and exogenous variables.

Historical simulation

The role of historical simulations is primarily to uncover the unobservable structural change characteristics – changes in technology and tastes – from historical data. Such an information is useful in generating forecasts (baseline solutions) with a CGE model. Historical simulations are facilitated by appropriate model closure – the so called historical closure – which differs significantly from the ones used to simulate policy shocks. Many naturally endogenous variables, on which historical data are available, are exogenized, including a number of industry/commodity-level variables (as well as some macro-variables). Exogenizing those variables requires freeing the equal number of other variables that will adjust to shocks applied to the former ones. Different variants of a historical closure are possible, as far as the choice of exogenized variables and the "absorbers" is concerned. This choice usually depends on data availability, as well as relies on a few arbitrary assumptions. The historical closure used in our simulations is characterized in Table 1. The left column shows the groups of exogenized variables, while the right column shows compensating mechanisms that the model needs to employ to fit into the fixed paths of the exogenized variables (shown in the left column).

To perform a historical simulation, two observations normally suffice (referring to two distant periods). However, the simulation discussed in this paper is year-to-year, covering the period 2000-2005. The model is solved recursively, so the movements (percentage changes) of the observed variables between 2000 and 2001 are accommodated by movements in taste, technology and related variables[1] in the same period, and so on. Full results of the historical simulation are presented in the Annex.

[1] We prefer to refer to the quantities in question as 'variables' rather than 'parameters', as this reflects how they are really implemented in our experiment. However, these are in fact parameters (i.e. they are fixed) in the typical policy simulation context.

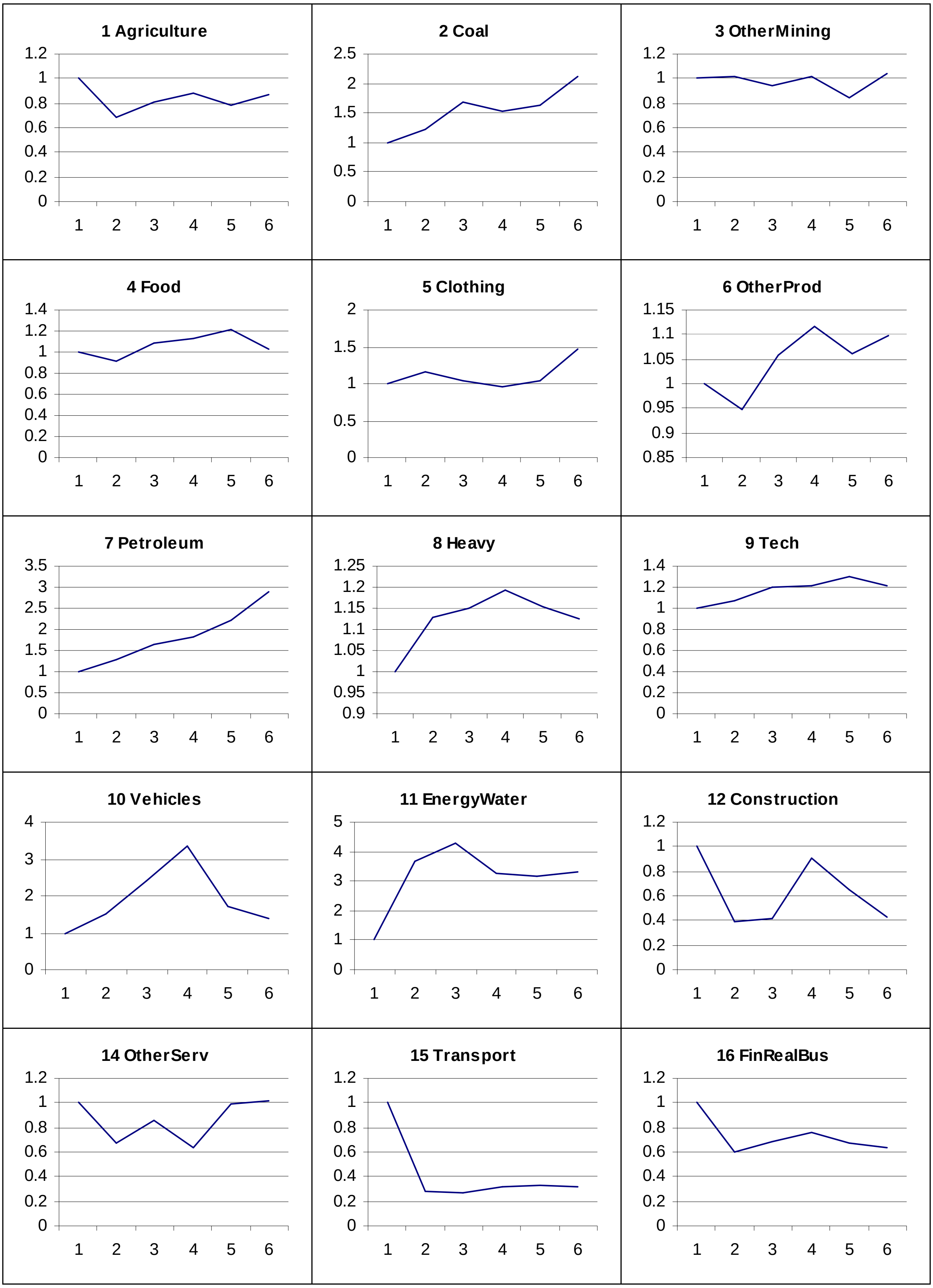
Table 1. Characteristics of the historical closure

Exogenized movement	**Accommodated by**
Industry/commodity level variables	
Fixed capital formation	Shift in rate of return required to pursue a given amount of investment
Fixed capital stocks	Adjustment of the assumed depreciation rates of capital in a given year
Employment	Shift in joint primary factors' productivity
Wage bill	Varied wage movements across industries
Capital rentals	Technological shift in capital/labor ratio
Industry output	Input (commodity) saving/using technical change; change in use of trade margins
Household consumption	Change in household tastes
Exports	Autonomous shift in foreign demand
Local-currency import prices	Foreign-currency import prices
Imports (current prices)	Preference/technology shift between domestic and imported commodities
Aggregate variables	
Aggregate household consumption	Consistency adjustment of consumption by commodities to aggregate data
Aggregate exports	Consistency adjustment of exports by commodities to aggregate data
Aggregate imports	Consistency adjustment of imports by commodities to aggregate data

As an example, consider the so called twists in domestic/import choice (see Dixon and Rimmer, 2002, p. 173-179). The twist is interpreted as the change in the ratio of imports to domestic output that cannot be explained (within a given model specification and for a given Armington elasticity) by changes in relative prices. In our model an increase in the twist variable for a given commodity is interpreted as a taste shift towards imports, at the expense of domestic production. The cumulated import-domestic twists resulting from our simulation are shown in Figure 1 (non-import commodities are excluded).

The results suggests that year-to-year "preference" twists between imported and domestic commodities are rather large and volatile (although a general tendency in favor of imports is also evident). From the point of view of year-to-year forecasting it is an adverse situation. Accurate forecasting requires that we are able to explain (endogenize) these twists. Identifying their systematic part – e.g. relying on trends – might serve as a starting point. The non-systematic part would then be treated as errors. In fact, Hillberry et al. (2005) have already proposed that in certain contexts one could treat model parameters as residuals.

Figure 1. Cumulative import-domestic twists. Results from the historical simulation.



Two interesting questions arise. Firstly, how reliable are year-to-year forecasts under such generally irregular changes in technology and taste variables (the irregularities are inherent in many of the technology and taste variables – see the Annex). We shall refer to that point in the next section. The second, and more general question is whether and how could we diminish the "irregular" part of variation of technology and taste variables.

It seems useful to think about three component of the non-systematic variation of technology/taste parameters – (1) a "truly exogenous" part (that a CGE-like model cannot explain), (2) a part arising due to specification and parameter errors, and (3) a part related to poor data quality. The third point might be a problem in our case, as we found inconsistencies between disaggregated and aggregate data (hence the consistency adjustment terms – see Table 1). We shall investigate this in our further research. Concerning the second point, we think that the combined year-to-year historical and forecast simulations could serve as a framework for testing the model's specification and parametrization.

Forecast simulations

In principle, the forecast closure is similar to the historical closure. The difference between them is mainly about the context of their use – forecast simulations normally relate to those periods, for which only limited data are available – i.e. mainly the data (or forecasts, if the baseline solution is for future periods) for macro categories. The variables that accommodate exogenous changes in macro variables, are, similarly to historical closure, broadly the technology and taste change variables – but their endogenous adjustments are now uniform across industries/commodities (see Table 2).

Table 2. Characteristics of the forecast closure

Exogenized movement	**Accommodated by**
Aggregate household consumption	Average propensity to consume
Aggregate exports	Uniform shift in foreign demand
Aggregate imports	Uniform preference/technology shift between domestic and imported commodities
Nominal exchange rate	Uniform change in primary factor productivity
Aggregate employment	Real wage
Industry/commodity level variables	
Fixed capital formation	Shift in rate of return required to pursue a given amount of investment
Fixed capital stocks	Adjustment of the assumed depreciation rates of capital in a given year

As we could not hitherto reconcile the data on industry capital stocks and investment to calibrate sensible capital accumulation equations, we decided to keep both categories exogenous, as in the historical closure. This would rather be impossible in ex ante forecasting, but is admissible for ex posts forecasts. Similarly, we treat government consumption, as well as foreign prices as exogenous. On the other hand, the model in the forecast mode calculates the changes of a number of other industry/commodity level variables – consumption, exports, imports, output, employment, domestic prices etc. – which is where the typical CGE mechanisms, like factor substitution, import-domestic substitution, consumption and export responses to relative price changes etc. come into play.

Forecast simulation allows us to use the results from historical simulation. For example, we can apply differentiated import-domestic twists at the commodity level as exogenous shocks. Literally doing it with all technology and taste variables endogenized in the historical closure would lead to exactly reproducing historical results for all of model's variables. However, in the forecasting context (as well as in the context of ex post forecast verification) it is reasonable to assume that we know only the systematic part of the "structural change". The systematic part here is treated as an average annual rate of growth of a given technology or taste (or other shift) variable during the period 2000-2005 (with exception made for three evident outliers which were related to changes in the scope of data definition). In such a way we obtain a picture of smoothed structural change (as opposed to actual 'structural change', as illustrated in Figure 1). We shall refer to it as **forecast simulation 1**.

Another option in forecast simulations is to rely totally on the data, and abandon any use of historical simulation results (typical if no such results are available). In such a case the model determines technology and taste shifts, but it does not differentiate them between industries. We should expect these forecasts to be generally less accurate than under the previous option. We shall refer to this option as **forecast simulation 2**. Comparison with forecast 1 should reveal how much gain there is from the (smoothed) historical simulation results .

Forecast simulation 3 is a variant of simulation 1, in which Armington elasticities, originally based on literature review, were substituted with the values estimated (or perhaps the term 'calibrated' would me more appropriate) using the 2000-2005 data for Poland. Comparison with simulation 1 should show an example of possible gains from using a more adequate parameter set.

Testing the forecast performance we focus on results for industry outputs and prices. The following two simple performance (error) measures are applied (see Dixon and Rimmer, 2010):

$$E = \frac{1}{N \cdot T} \cdot \sum_{i,t} \left| f_{it} - a_{it} \right| \tag{1}$$

$$WE = \frac{1}{N \cdot T} \cdot \sum_{i,t} W_{it} \cdot \left| f_{it} - a_{it} \right| \tag{2}$$

where f_{it} is forecasted percentage change in output (price) in industry *i*, in year *t*; a_{it} is actual percentage change in output (price) in industry *i*, in year *t*; *N* is the number of industries, *T* – number of years in the forecast simulation; *W* – optional weights of individual errors (we use actual industry outputs in current prices as weights). *E* measures average difference between actual and forecasted percentage changes of variables of interest. In turn, *WE* gives larger weights to variables (e.g. industry outputs) having higher shares in their aggregate (e.g. aggregate output).

Both error measures should be compared with average actual percentage changes (unweighted and weighted, respectively) of industry outputs, i.e.:

$$A = \frac{1}{N \cdot T} \cdot \sum_{i,t} |a_{it}| \qquad (3)$$

$$WA = \frac{1}{N \cdot T} \cdot \sum_{i,t} W_{it} \cdot |a_{it}| \qquad (4)$$

Table 3. Average errors of forecast simulations (in p.p.) and actual average changes of forecasted variables (in %).

	Industry output		Prices of industry output	
	E	WE	E	WE
Simulation 1	4.98	3.95	7.20	5.36
Simulation 2	5.76	4.22	7.50	5.81
Simulation 3	4.59	3.90	6.56	5.35
	A	WA	A	WA
Actual average change (%)	5.33	4.81	6.80	5.25

The results are reported in table 3. As can be seen, average errors are relatively large. In forecast 1 average unweighted error for percentage changes of industry output is 4.98 p.p., which is over 93% of actual average percentage changes (5.33%). The results look only slightly better when weighted averages are taken into account (average error equal to 82% of actual average percentage change). The results are even more pessimistic for prices, where average errors exceed actual average percentage change in all cases but one (simulation 3).

The model generally performs better when utilizing information from historical simulations ("smoothed" changes in technology and taste variables), although the difference is not striking – compared to simulation 2 the errors are reduced by 4%-14% in simulation 1. Employing the estimated – instead of literature based – Armington elasticities further reduces the unweighted errors by 8%-9% - but not the weighted ones. In all, the results must be referred to as rather disappointing, especially taking into account a relatively big load of actual movements (industry capital and investment, government consumption) used as shocks.

Concluding remarks

The results of CGE-based policy analysis are affected by benchmark equilibrium data. The fact that such data are published with a substantial time-lag forces CGE users to predict the economy's industry/commodity structure. The quality of such forecasts depends on projections related to the exogenous part of the model – including (industry/commodity specific) technical change, taste shifts, foreign demand shifts etc. Preparing such projections can be aided by historical simulations, which help quantify structural changes (shocks) in the past. However, the results of historical simulations are also contaminated by model's specification, parametrization, and data errors (in other words, varying model's specification and parameter values would lead to diverse results of a historical simulation, and thus different pictures of structural change).

Ideally, the truly exogenous shifts should be separated from the errors. In this paper we operationalized this split by assuming that only the systematic (trend) changes form the true structural change. Removing the non-systematic variation of technology and taste variables (smoothing) in the year-to-year ex post forecast experiment clearly leads to errors in endogenous results – analogous to residuals from the econometric framework. The errors that we obtained for industry variables (namely output and prices) in such a setting were serious. They were not much smaller than in the forecast simulation that did not employ any historical results at all. We also showed, by an example of Armington elasticities, how errors might be reduced by using more appropriate parameter values. It seems that the major source of problems is the poor performance of export and import equations (relatively large irregular shifts in foreign demand and import/domestic twists are required to fit the volatile data). These results leads us to the following conclusions, which at least hold for an economy characterized by volatile movements of industry/commodity variables (an emerging or post-transition economy, such as Poland):

- A historical simulation revealed that in order to make the model reproduce actual movements of industry commodity variables in a year-to-year setting one needs to supply much extraneous information, including large and rather irregular changes of various technology and taste variables. These results do not suggest that behavioral features included in CGE models are not valid, but rather that their effects are perhaps overwhelmed by numerous and simultaneous exogenous shocks.

- Supplying technology and taste changes just in their systematic (and thus more easily predictable) part does not lead to satisfactory year-to-year forecast. However, evident trends in most of technology and taste variables lead us to expect that longer-run forecast might be more reliable.

- The question for further research is to what extent changes in model specification and parametrization (while not going beyond a typical CGE feature set – e.g. cost-minimizing or utility maximizing behavior, representation of industry technological constraints etc.) could improve CGE year-to-year forecasting performance. Possibly the presented approach could serve as a validation framework, at least for the model's short-run mechanisms.

References

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Annex – structural change characteristics resulting from historical simulations

Figure 2. Primary factor saving technical change (decrease = productivity improvement)

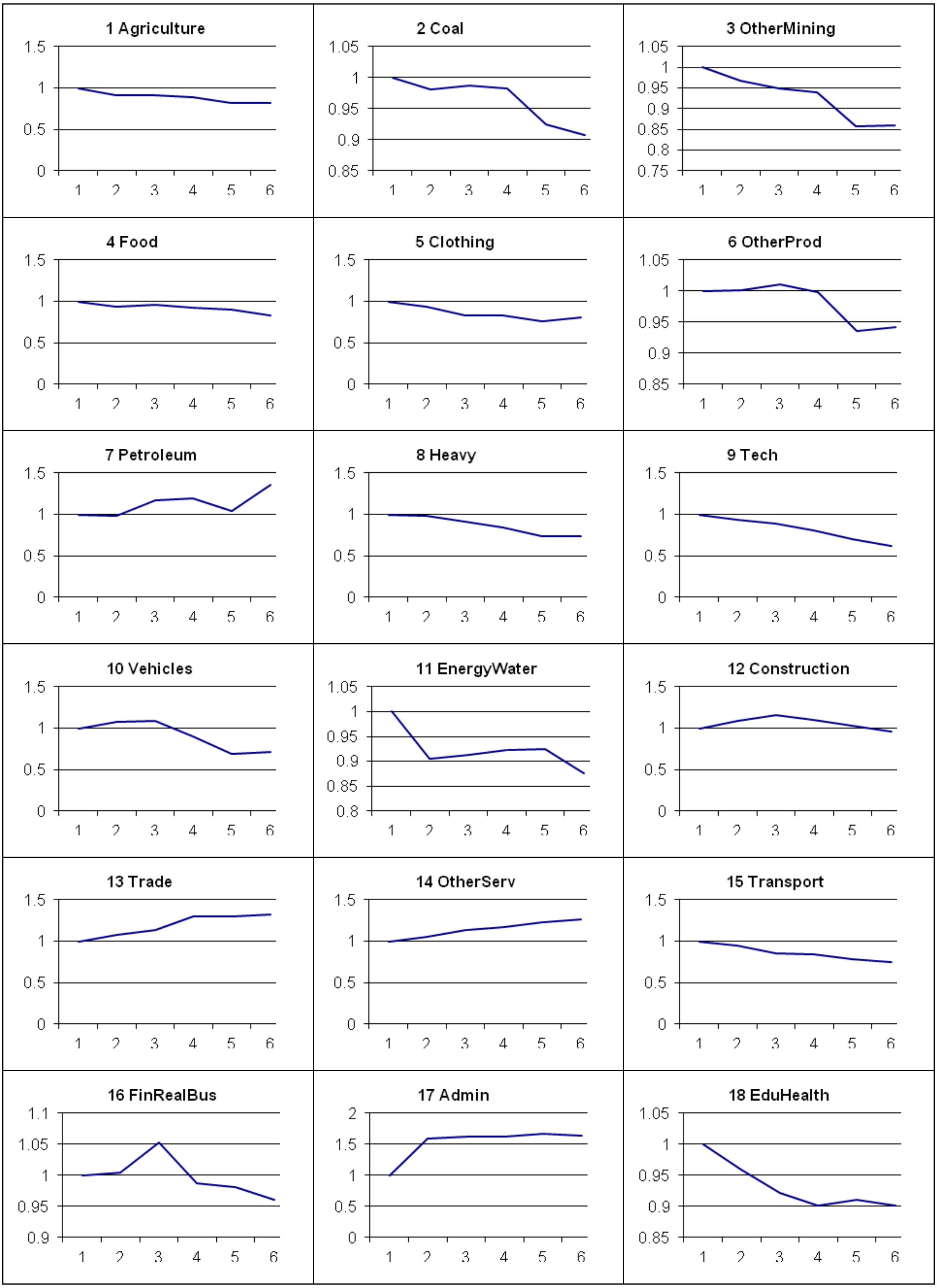

Figure 3. Changes in household tastes for commodities

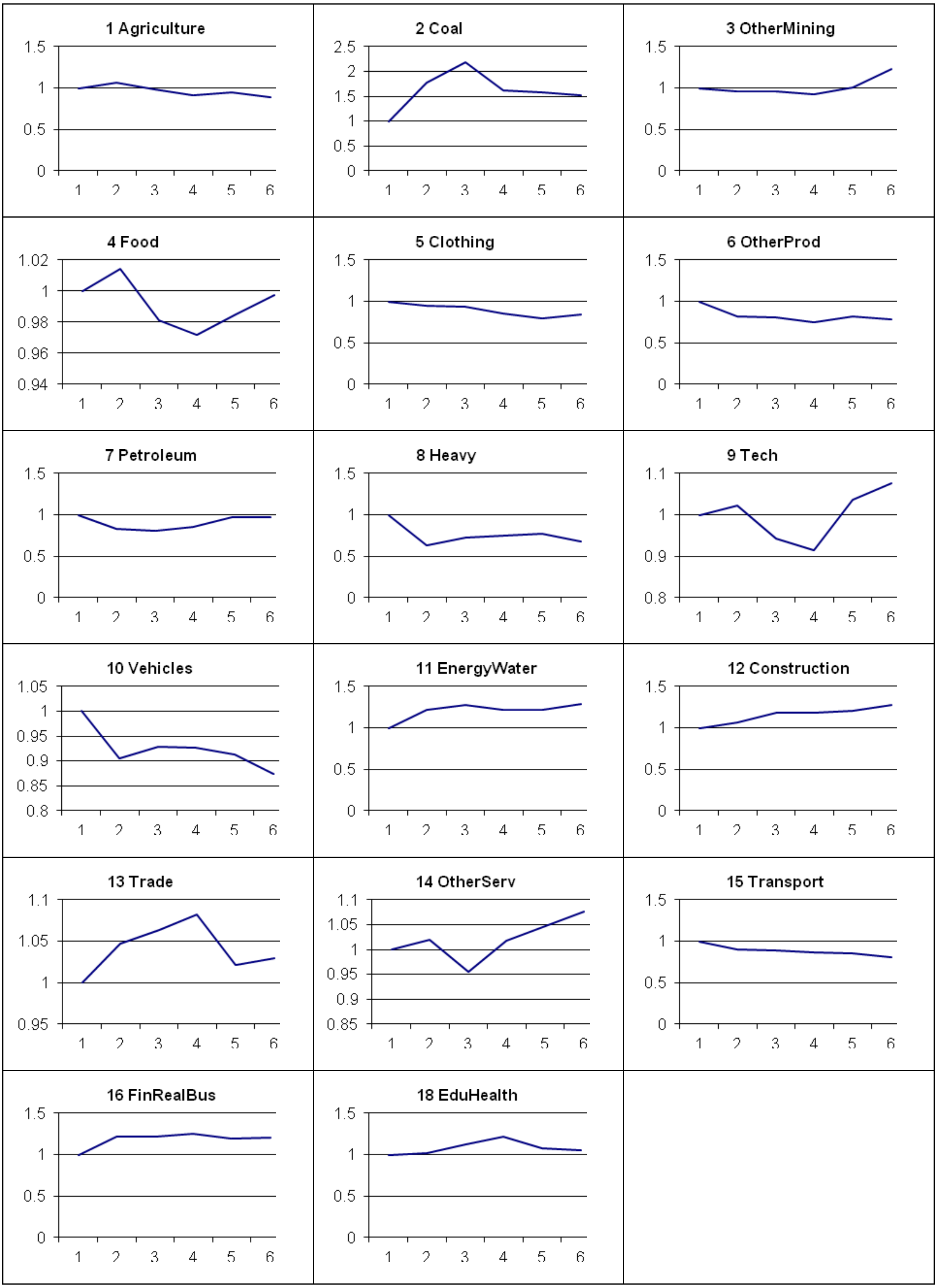

Figure 4. Shifts in labor-capital ratio

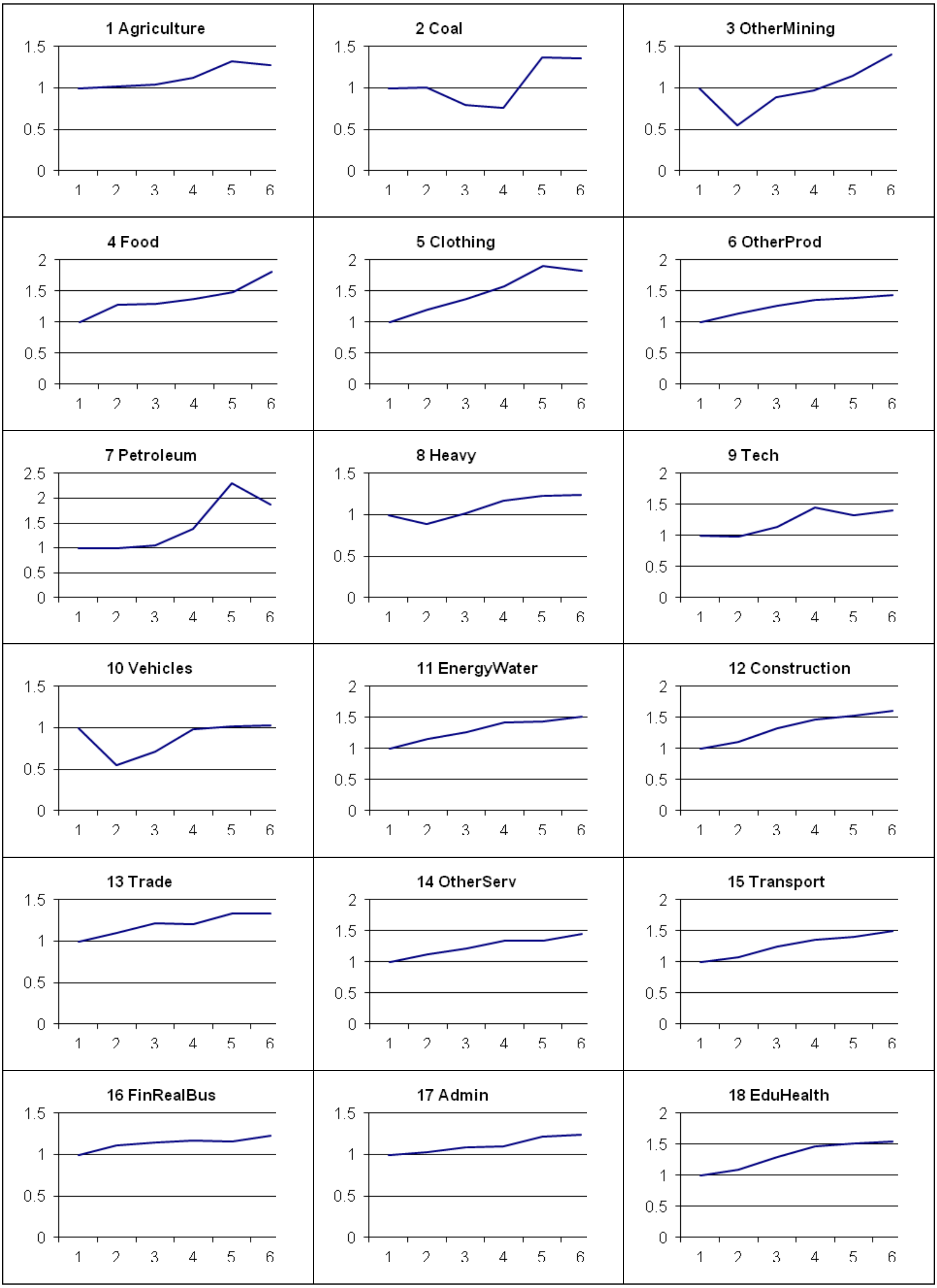

Figure 5. Price-independent shifts in foreign demand

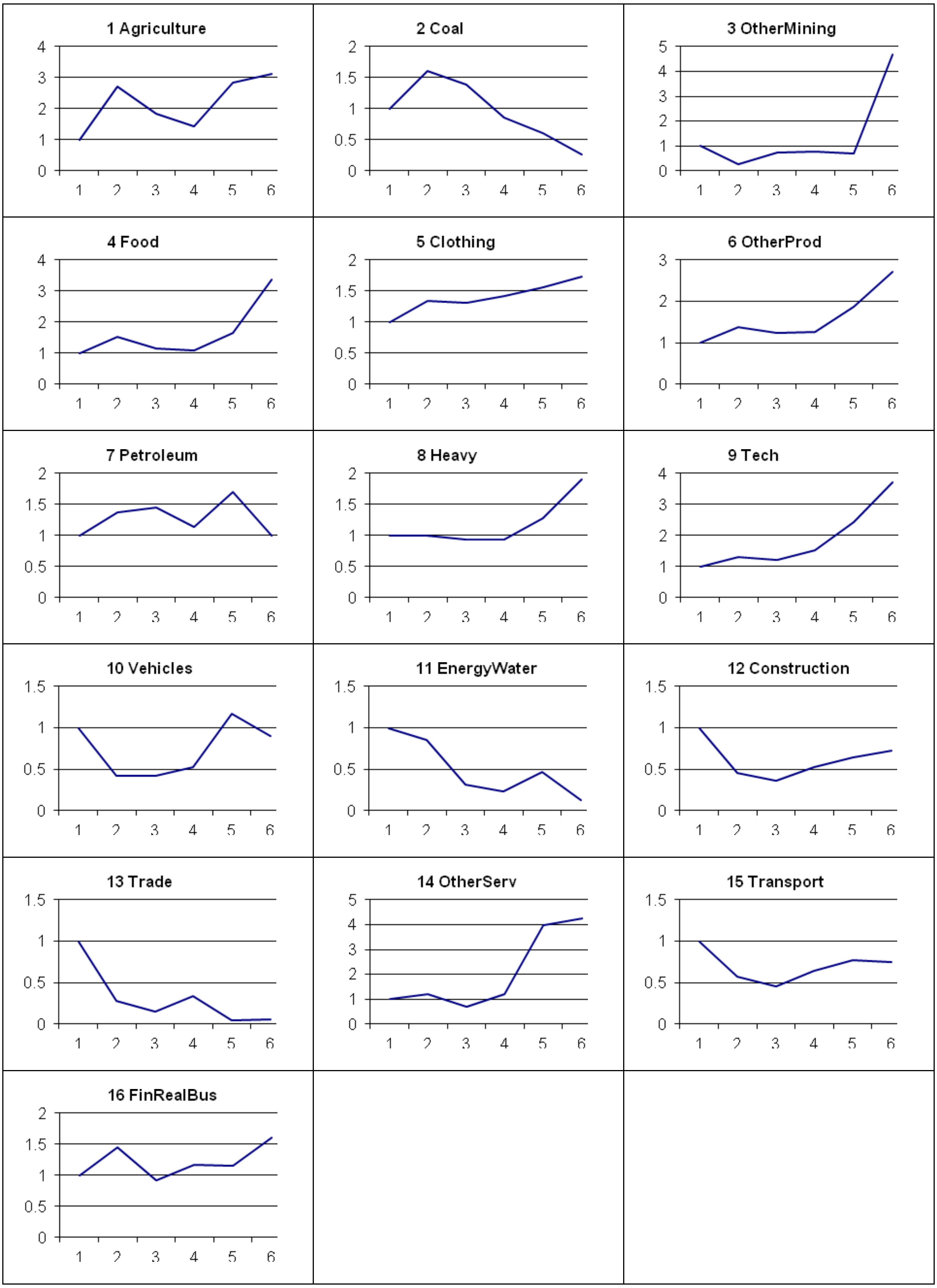

Figure 6. Wage shifts (differentiating wage changes across industries)

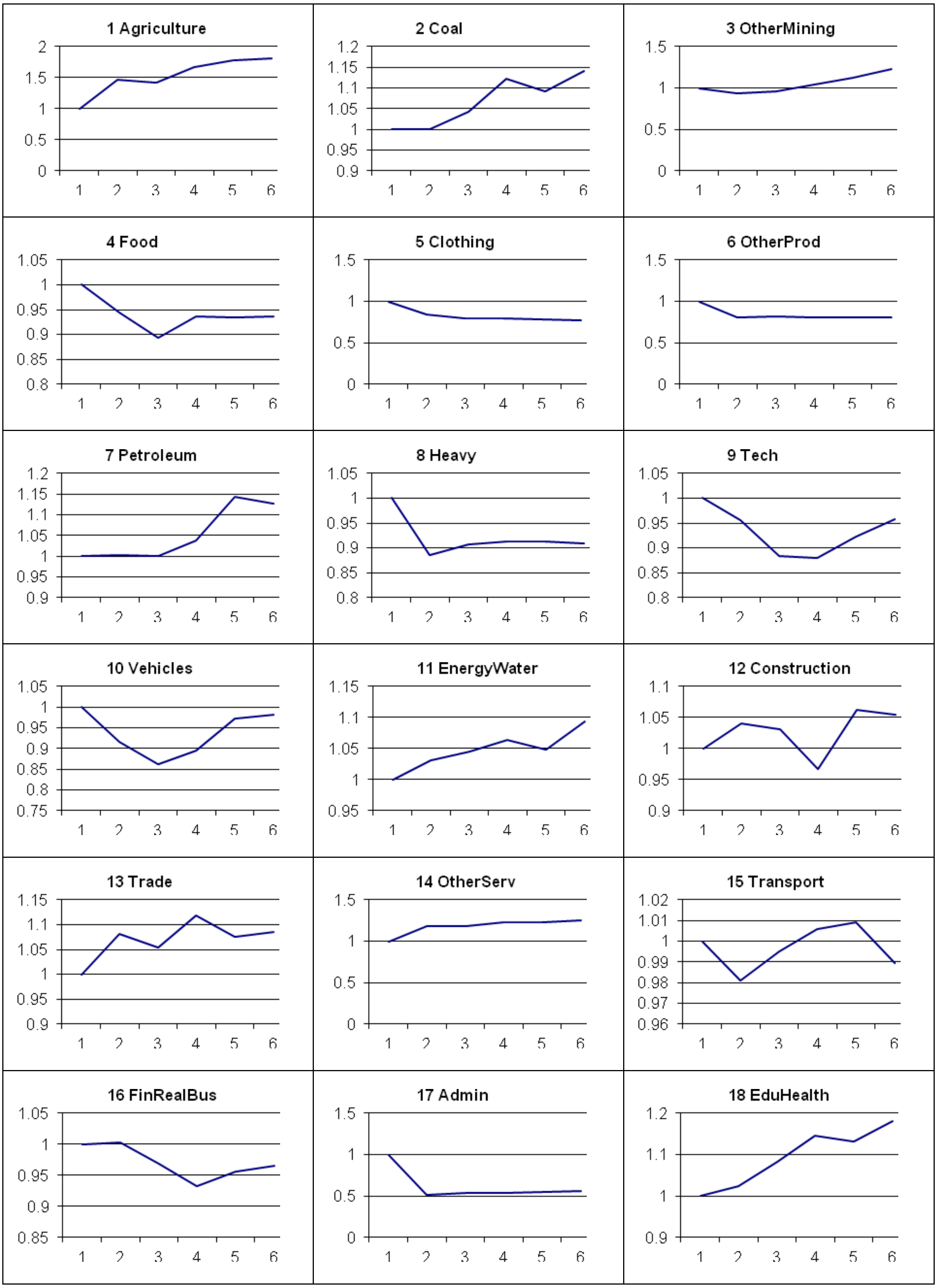

Figure 7. Input (commodity) saving technical change (negative=productivity increase); Trade – changes in margin uses