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Connectionist-based rules describing the pass-through of individual goods prices into trend inflation in the United States

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ABSTRACT

This paper examines the inflation "pass-through" problem in American monetary policy, defined as the relationship between changes in the growth rates of individual goods and the subsequent economy-wide rate of growth of consumer prices. Initial relationships are established with Granger causality tests robust to structural breaks. A feedforward artificial neural network (ANN) is used to approximate the functional relationship between selected component subindexes and the headline CPI. Moving beyond the ANN "black box", we illustrate how decision rules can be extracted from the network.

1. Introduction: the inflation pass-through problem

This study explores the "inflation pass-through problem," that is, how large (if any) is the subsequent change in the headline or core (excluding food and energy) inflation rate following an abrupt increase or decrease in the rate of change of the price of a specific commodity or group of commodities. We examine Granger causality tests robust to structural breaks, and extract sets of "human readable" rules from an artificial neural network (ANN). The functional relationship between aggregate price indexes and individual prices (or subindexes) is unknown and likely nonlinear, motivating the use of an ANN. The aggregate index is a function of time-varying expenditure shares as well as individual-commodity prices. In some cases the "individual" prices are themselves price indexes (such as the BLS price indexes for energy, transport, and housing) which are not proper subsets of the aggregate index. The strength of pass-through also depends on the monetary authority's inflation targeting regime (e.g. Bernanke et al., 1997), with pass-through likely small when the authorities have a credible inflation target.

We focus on price (sub)indexes for energy, food, housing and transport prices.[1] Energy is an essential input to housing and transport, although only one of a number of inputs. Intermediate, perhaps, are food prices because less expensive food products may be substituted when prices increase sharply. Our work is related to the literature on oil price shocks which has concluded that the relationship between oil prices and economic activity (including inflation) is time-varying, nonlinear, and asymmetric. Studies specifically addressing passthrough include Hooker (2002), van den Noord and Andr (2007), De Gregorio et al. (2007), Cecchetti et al. (2007), Blanchard and Gali (2010), Chen (2009), and Clark and Terry (2010).

2. Empirical analysis of passthrough

Table 1 reports p-values for both direct Granger causality (GC) (panel A) and reverse GC (panel B) using Rossi's (2005) test statistic robust to parameter instability; our testing strategy

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[1] Our data are the Bureau of Labor Statistics's Consumer Price Index "Research Series" (CPI-U-RS) in which indexes have been constructed for historical dates using the same definitions and methods used for newly published data (Stewart and Reed, 1999). We include the aggregate CPI and subcomponent indexes for food, energy, housing, and transportation. Our figures are the monthly percentage change from the same month one year earlier, not-seasonally-adjusted, from December 1977 to December 2009.

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Table 1
Granger causality tests robust to instabilities (Rossi, 2005).

	Energy	Transport	Housing	Food
Tests for headline CPI, denoted as "cp"				
Panel A:	p-values for $H_0: \gamma_j = \gamma = 0$ in $\Delta cp_{t+1} = \alpha + \sum_{j=0}^{N} \beta_j \Delta cp_{t-j} + \sum_{j=0}^{N} \gamma_j \Delta z_{t-j}$			
$N = 13$	0.025**	<0.01***	0.029**	>0.10
$N = 25$	0.070*	<0.01***	0.082*	0.036**
Panel B:	p-values for $H_0: \gamma_j = \gamma = 0$ in $\Delta z_{t+1} = \alpha + \sum_{j=0}^{N} \beta_j \Delta z_{t-j} + \sum_{j=0}^{N} \gamma_j \Delta cp_{t-j}$			
$N = 13$	>0.10	0.043**	<0.01***	0.043**
$N = 25$	>0.10	>0.10	0.027**	0.096*
Tests for Core CPI (headline CPI excluding food and energy), denoted as "cp"				
Panel A:	p-values for $H_0: \gamma_j = \gamma = 0$ in $\Delta cp_{t+1} = \alpha + \sum_{j=0}^{N} \beta_j \Delta cp_{t-j} + \sum_{j=0}^{N} \gamma_j \Delta z_{t-j}$			
$N = 13$	0.051*	>0.10	0.050**	0.071*
$N = 25$	>0.10	>0.10	>0.10	>0.10
Panel B:	p-values for $H_0: \gamma_j = \gamma = 0$ in $\Delta z_{t+1} = \alpha + \sum_{j=0}^{N} \beta_j \Delta z_{t-j} + \sum_{j=0}^{N} \gamma_j \Delta cp_{t-j}$			
$N = 13$	>0.10	>0.10	0.042**	0.025**
$N = 25$	>0.10	>0.10	>0.10	>0.10

The table reports p-values for the null hypotheses that each of the four component price indexes does not Granger-cause the headline or core CPI, adjusted for instabilities as in Rossi (2005). We test at two lag lengths: the AIC generally suggested 24 lags, the BIC suggested 12. For robustness, we increase each lag by one.

* Indicate rejection of the null at 10% level.

** Indicate rejection of the null at 5% level.

*** Indicate rejection of the null at 1% level.

follows Chen et al. (2010).[2] The specific statistic we consider is the Lagrange multiplier form of the robust Andrews–Quandt optimal test, QLR_T^* (Rossi, 2005, equ 27). Where possible, p-values are linearly interpolated between the asymptotic critical values in Rossi (2005), table B.3, p. 990. Where test statistics fall outside the bounds of her table, the p-values are denoted "<0.01" or ">0.10". For headline CPI and direct causality (panel A), we reject at the 10% level the null of no GC by energy, transport and housing at both lag lengths, and for food at the 5% level for the longer lag. In panel B (reverse causality), we reject at the 5% level the null of no GC for transport, housing and food at the shorter lag, and for housing at the longer lag. Inference regarding housing continues to be clouded by strong reverse GC. In the lower half of Table 1 for core CPI, in panel A, the null of no GC is rejected for energy, housing and food at the shorter lag length; in panel B (reverse causality), the null is rejected for housing and food at the shorter lag. The results that the relationships between headline and core CPI, and between the energy and transport price subindexes, are sufficient to warrant further exploration. Food prices also have support, but due to the sensitivity of the results to lag length we leave them as a topic for future research. The results suggest that the relationships between headline and core CPI, and the energy and transport component subindexes, are sufficiently reliable to warrant further exploration.

3. Connectionist neural networks[3]

The popularity of ANNs in economics is due to the ANN's ability to approximate an unknown continuous real-valued function to an arbitrary level of accuracy and to perform classification for decision regions that are not convex (e.g. Hornick et al., 1989). Recent papers (excluding forecasting) include: for inflation, Binner et al. (2010) and Nakamura (2005); for financial economics, McNelis (2005), Blynski and Faseruk (2006), and Geweke and Amisano (2011); and for approximating first-order conditions in solving DSGE macroeconomic models, Lim and McNelis (2008).

ANN should not be regarded as black boxes, with the analyst unconcerned with the internal workings of the network (e.g. Swanson and White, 1995, 2007). One technique for doing so is rule extraction from the network, which dates from Andrews et al. (1995) and Towell and Shavlik (1993). A comprehensive set of rules provides the same mapping from inputs to outputs as is provided by the connectionist model (ANN) itself. Constraints prevent the system's extracted rules from suggesting unreasonable choices. Algorithms for ANN rule extraction require that data be discretized prior to network training. The transportation and energy price indexes were classified into 12 and 17 ranges, respectively, labeled in Table 2 as A–L and M–AC, while aggregate inflation was discretized into six output ranges/nodes numbered 1–6 in the right-most section of Table 2. The model, hence, has 29 (12 +17) inputs and six outputs. All tested networks produced accuracy in the range of 87%–89% for training data, and 82%–84% for testing data; for discussion of the estimation of the ANN, see Anderson et al. (2011).

4. Analysis of the extracted rules

We obtain 25 extracted rules via a decompositional rule extraction algorithm (Schmidt, 2002; Schmidt and Philip Chen, 2002). The rules correspond to the columns in Table 3; output node 3 has the fewest, 3, and output node 4 has the most, 6. For each output node, the algorithm identifies those nodes within the (single) hidden layer that feed the specific output node; next, the algorithm identifies the input nodes that feed each of those hidden-layer output nodes, etc. In this manner, the algorithm iteratively constructs a mapping from the input nodes to the output nodes. The output rules are straightforward to interpret as if–then–else constructions. Rules 1–4, for example, map to output node 1: inflation less than or equal to 1.25% per annum. Rules 5–8, for example, map to output node 2: inflation between 1.25% and 2%. Note that node 3, corresponding to headline inflation between 2% and 3%, has the smallest number of rules (3), rules 9, 10 and 11. These rules, as a group, display the weakest dependence of headline inflation on movements in energy and transport prices.

[2] We conducted extensive lag-length selection experiments for all six price indexes. Beginning with a lag of six periods, tests (AIC, BIC) suggested a lag of one period. Beginning with a lag of 40 periods, the tests select lag lengths of 12 and 24 periods, respectively. For robustness, the tables display lag lengths of 13 and 25 periods. The data are year-over-year percentage changes, monthly. Tables containing similar results for standard Granger causality and Andrews–Quandt tests, omitted here for brevity, are included in Anderson et al. (2011).

[3] The label "connectionist" was introduced by Feldman and Ballard (1982) to describe the use of neural networks as statistical tools, with little (if any) reference to biology or human physiology.

Table 2
Input and output ranges, and observations per range (combined training and test datasets).

Input and output ranges, and number of observations per range											
Transportation ranges			Number of observations	Energy ranges			Number of observations	Output ranges			Number of observations
	Lower bound<=	Upper bound<			Lower bound<=	Upper bound<			Lower bound<=	Upper bound<	
A	−Inf	−0.121254	7	M	−Inf	−0.265215	2	1	−inf	0.0125	19
B	−0.121254	−0.101202	2	N	−0.265215	−0.204803	6	2	0.012500	0.020000	48
C	−0.101202	−0.070711	2	O	−0.204803	−0.107416	21	3	0.020000	0.030000	113
D	−0.070711	−0.032497	17	P	−0.107416	−0.022121	38	4	0.030000	0.050000	134
E	−0.032497	−0.011131	25	Q	−0.022121	0.050777	155	5	0.050000	0.090000	30
F	−0.011131	0.014684	41	R	0.050777	0.106695	54	6	0.090000	inf	29
G	0.014684	0.074562	217	S	0.106695	0.138965	18				
H	0.074562	0.135777	40	T	0.138965	0.163726	22				
I	0.135777	0.166635	11	U	0.163726	0.185737	15				
J	0.166635	0.192465	6	V	0.185737	0.215139	14				
K	0.192465	0.220937	3	W	0.215139	0.253502	11				
L	0.220937	Inf	2	X	0.253502	0.282514	1				
				Y	0.282514	0.321399	4				
				Z	0.321399	0.371623	6				
				AA	0.371623	0.409081	2				
				AB	0.409081	0.447016	2				
				AC	0.447016	Inf	2				

Table 3
Graphical representation of extracted rules.

Input range	Graphical representation of ranges used in output nodes (rules)																										
			Output nodes																								
			Node 1 [−inf, 0.0125]				Node 2 (0.0125…2.0]				Node 3 (2.0…3.0]			Node 4 (3.0…5.0]						Node 5 (5.0…9.0]				Node 6 (9.0…Inf]				
	Rule number >		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
	Transportation ranges																											
A	−Inf	−0.121254	X																					X				
B	−0.121254	−0.101202		X			X																	X				
C	−0.101202	−0.070711			X		X							X						X				X				
D	−0.070711	−0.032497			X			X							X					X					X			
E	−0.032497	−0.011131							X		X				X					X				X				
F	−0.011131	0.014684								X		X				X				X				X				
G	0.014684	0.074562					X						X				X				X					X		
H	0.074562	0.135777					X											X				X		X				
I	0.135777	0.166635			X														X	X							X	
J	0.166635	0.192465				X																	X					X
K	0.192465	0.220937			X																		X					X
L	0.220937	Inf			X															X								X
	Energy ranges																											
M	−Inf	−0.265215		X	X				X											X	X	X	X				X	
N	−0.265215	−0.204803		X		X		X	X											X	X	X					X	
O	−0.204803	−0.107416		X				X	X					X			X			X	X	X					X	
P	−0.107416	−0.022121		X				X	X			X					X				X	X					X	
Q	−0.022121	0.050777		X				X	X		X	X					X					X					X	
R	0.050777	0.106695		X				X	X		X	X		X								X					X	
S	0.106695	0.138965		X				X	X				X											X	X		X	
T	0.138965	0.163726		X				X	X	X		X				X	X					X			X		X	
U	0.163726	0.185737		X					X	X		X		X	X	X	X	X									X	
V	0.185737	0.215139		X					X	X		X		X	X	X	X	X									X	
W	0.215139	0.253502		X								X		X	X	X		X									X	
X	0.253502	0.282514		X				X	X	X				X							X	X					X	
Y	0.282514	0.321399		X								X		X	X	X		X									X	
Z	0.321399	0.371623		X			X	X	X	X									X									
AA	0.371623	0.409081												X	X	X	X							X	X	X	X	
AB	0.409081	0.447016												X	X	X	X							X	X	X	X	
AC	0.447016	Inf												X	X	X	X							X	X	X	X	

This is completely reasonable because observations during this period comprise much of the "Great Moderation." In contrast is output node 6, with a monthly headline CPI inflation rate exceeding 9%. Inflation at that rapid a pace was observed only in one epoch: May 1979 to September 1981, when inflation was consistently greater than a 9% annual rate and energy prices increased at a 20% annual pace in May 1979, a 47% pace in May 1980, and continuing at more than a 10% pace through December 1981. When energy price inflation once again reached a 20% rate in March and June 2000, the headline inflation was at a 3.7% pace.

Generally, we deem the transport rules as informative for output nodes 1–4: conditional on being within the range of a specific output node, observing the change in the transport price index informs future headline inflation. But energy prices are next to useless, a result that confirms previous results in the literature that variations in energy price inflation hold little predictive power for headline inflation.

5. Conclusions & future work

We have illustrated methods to open the black box that surrounds connectionist models (statistically oriented neural networks), and have illustrated them with an application to the inflation pass-through problem. We find rules in line with our priori expectations, based on extant empirical results in the economics literature.

Our results suggest that, from a policy perspective, there is almost no pass through from energy prices into trend headline inflation: although our estimated ANN/rule extraction methods suggest that energy should be included in a number of rules, the rules have a wide range of values. This is consistent with the economics literature: energy fluctuates so wildly that it is difficult to infer much from the fluctuations.

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References

Anderson, R.G., Binner, J., Schmidt, V., 2011. Connectionist-Based Rules Describing the Pass-through of Individual Goods Prices into Trend Inflation in the United States. Fed Res Bank of St. Louis Working Paper 2011-007A. February.

Andrews, R., Diederich, J., Tickle, A., 1995. Survey and critique of techniques for extracting rules from trained artificial neural networks. Knowledge Based Systems 8, 373–389.

Bernanke, B.S., Gertler, M., Watson, M., 1997. Systematic monetary policy and the effects of oil price shocks. Brookings Papers on Economic Activity 1, 91–142.

Binner, J., Tino, P., Tepper, J., Anderson, R., Jones, B., Kendall, G., 2010. Does money matter in inflation forecasting? Physica A: Statistical Mechanics and its Applications 389, 4793–4808.

Blanchard, O., Gali, J., 2010. The macroeconomic effects of oil price shocks: why are the 2000s so different from the 1970s? In: Gali, J., Gertler, M. (Eds.), International Dimensions of Monetary Policy. University of Chicago Press for the NBER, pp. 373–421.

Blynski, L., Faseruk, A., 2006. Comparison of the effectiveness of option price forecasting: black-sholes vs simple and hybrid neural networks. Journal of Financial Management and Analysis 19, 46–58.

Cecchetti, S.G., Hooper, P., Kasman, B., Schoenholtz, K., Watson, M., 2007. Understanding the Evolving Inflation Process. US Monetary Policy Forum Working Paper, Booth School of Business, University of Chicago.

Chen, S., 2009. Oil price pass through into inflation. Energy Economics 31, 126–133.

Chen, Y., Rogoff, K., Rossi, B., 2010. Can exchange rates forecast commodity prices? Quarterly Journal of Economics 125, 1145–1194.

Clark, T., Terry, S., 2010. Time variation in the inflation passthrough of energy prices. Journal of Money Credit Bank 42, 1419–1433.

De Gregorio, J., Landerretche, O., Neilson, C., 2007. Another pass-through bites the dust? Oil prices and inflation. Economía 7, 155–196.

Feldman, J., Ballard, D., 1982. Connectionist models and their properties. Cognitive Science 6, 205–254.

Geweke, J., Amisano, G., 2011. Hierarchical markov normal mixture models with applications to financial asset returns. Journal of Applied Econometrics 26, 1–29.

Hooker, M., 2002. Are oil shocks inflationary? Asymmetric and nonlinear specifications versus changes in regime. Journal of Money Credit Bank 34, 540–561.

Hornick, K., Stinchcombe, L., White, H., 1989. Multilayer feedforward networks are universal approximators. Neural Networks 2, 359–366.

Lim, G., McNelis, P., 2008. Computational Macroeconomics for the Open Economy. MIT Press.

McNelis, P., 2005. Neural Networks in Finance. Elsevier Academic Press.

Nakamura, E., 2005. Inflation forecasting using a neural network. Economics Letters 86, 373–378.

Rossi, B., 2005. Optimal tests for nested model selection with underlying parameter instability. Econometric Theory 21, 962–990.

Schmidt, V., 2002. An aggregate connectionist approach for discovering association rules. Ph.D. Thesis, Wright State University, Dayton, Ohio.

Schmidt, V., Philip Chen, C., 2002. Using the aggregate feedforward neural network for rule extraction. International Journal of Fuzzy Systems 4.

Stewart, K., Reed, S., 1999. Consumer price index research series using current methods, 1978–98. Monthly Labour Review 122, 29–38.

Swanson, N., White, H., 1995. A model selection approach to assessing the information in the term structure using linear models and artificial neural networks. Journal of Business and Economic Statistics 13, 265–275.

Swanson, N., White, H., 2007. A model selection approach to real-time macroeconomic forecasting using linear models and artificial neural networks. Review of Economic Statistics 79, 540–550.

Towell, G., Shavlik, J., 1993. The extraction of refined rules from knowledge-based neural networks. Machine Learning 131, 71–101.

van den Noord, P., André, C., 2007. Why Has Core Inflation Remained so Muted in the Face of the Oil Shock? OECD Econ Dept Working Papers, No. 551.