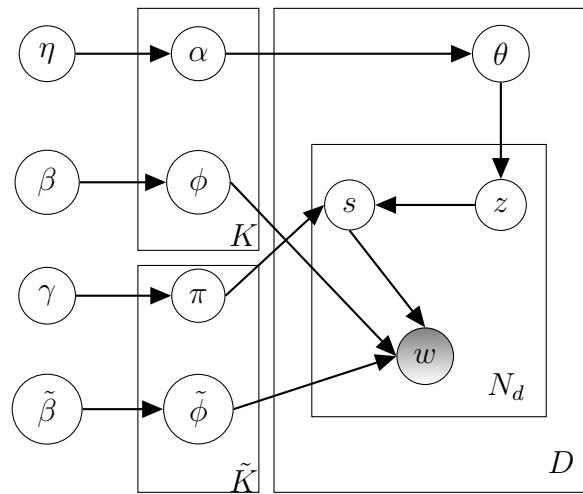


A Appendix - Going Viral: Inflation Narratives and the Macroeconomy

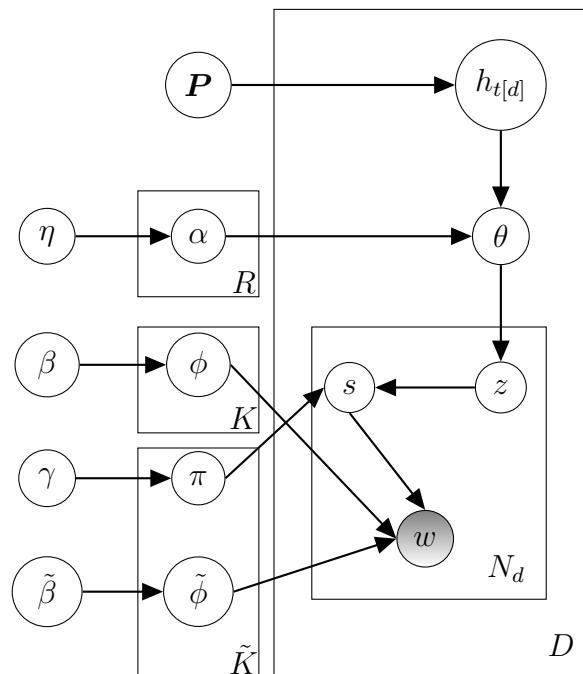
A.1 Supplementary Figures and Tables

Figure A.F.1: Graphical model of base keyATM



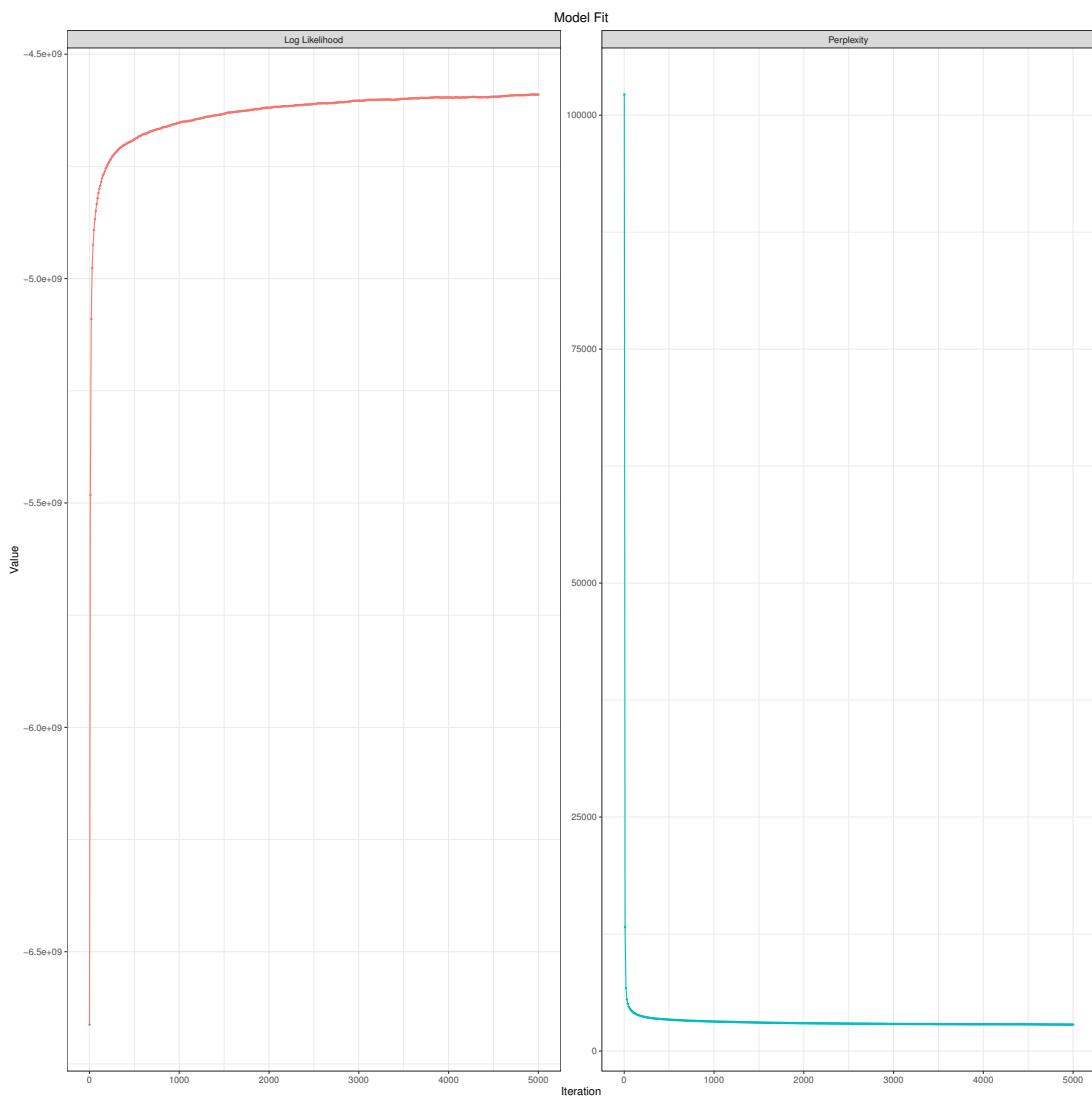
The shaded node (w) denotes observed variables, while other transparent nodes denote latent variables.
Source: (Eshima et al., 2020, 40)

Figure A.F.2: Graphical model of dynamic keyATM



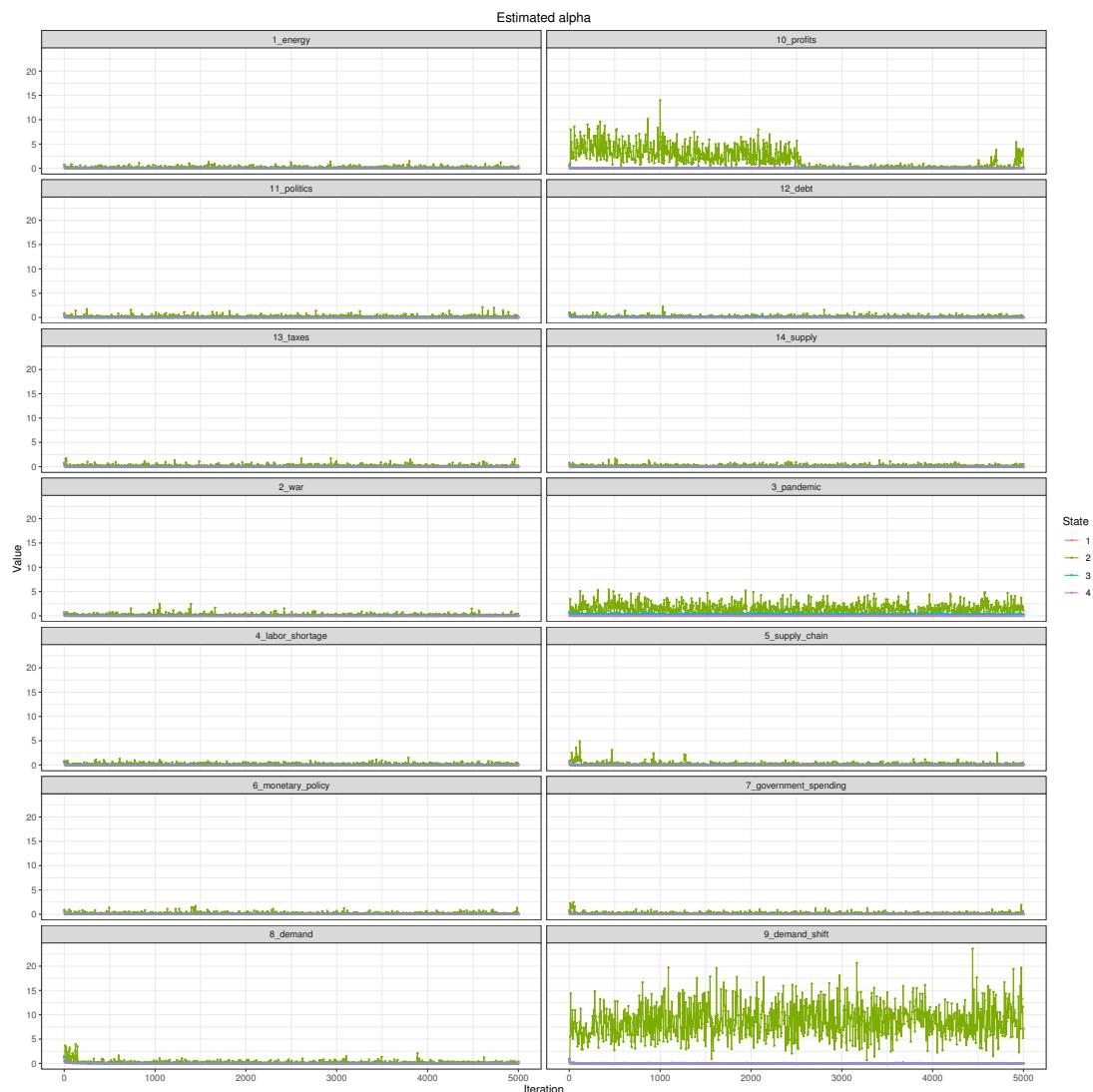
The shaded node (w) denotes observed variables, while other transparent nodes denote latent variables.
Source: (Eshima et al., 2020, 41)

Figure A.F.3: Modelfit



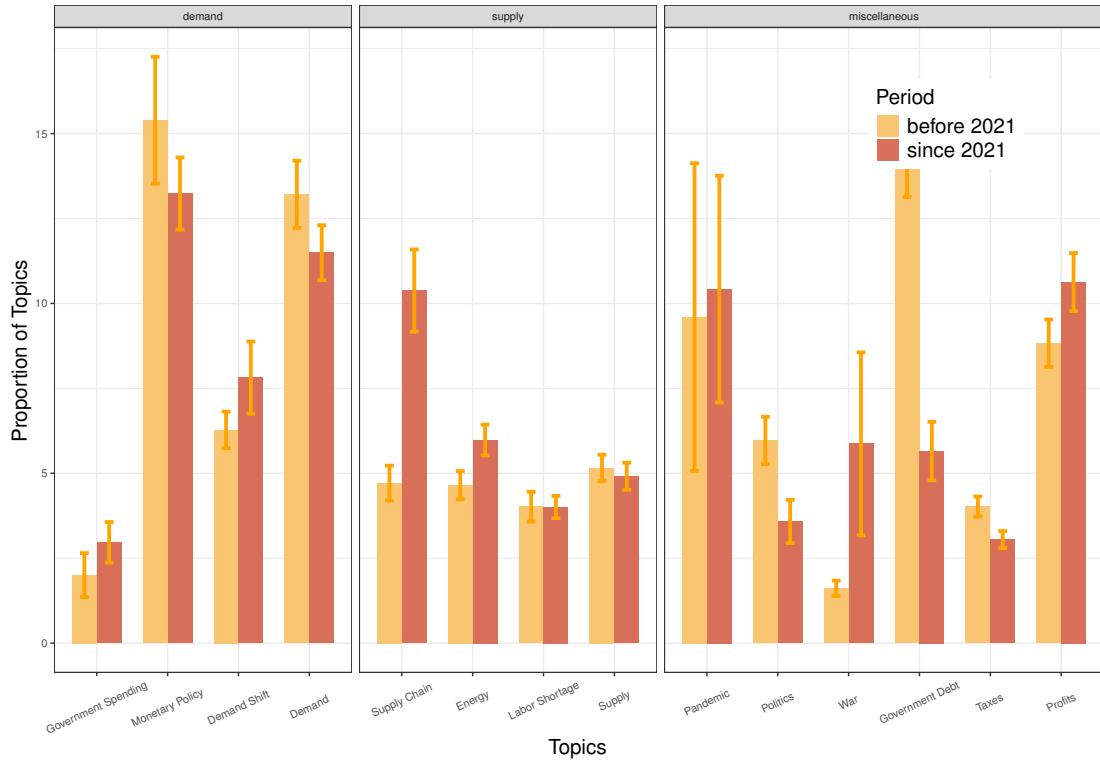
Note: The figure visualizes the model fitting. We observe an increase trend for the log-likelihood and a decrease trend for the perplexity, which is an indicator that the model is working as expected (Eshima et al., 2024).

Figure A.F.4: Estimated alpha



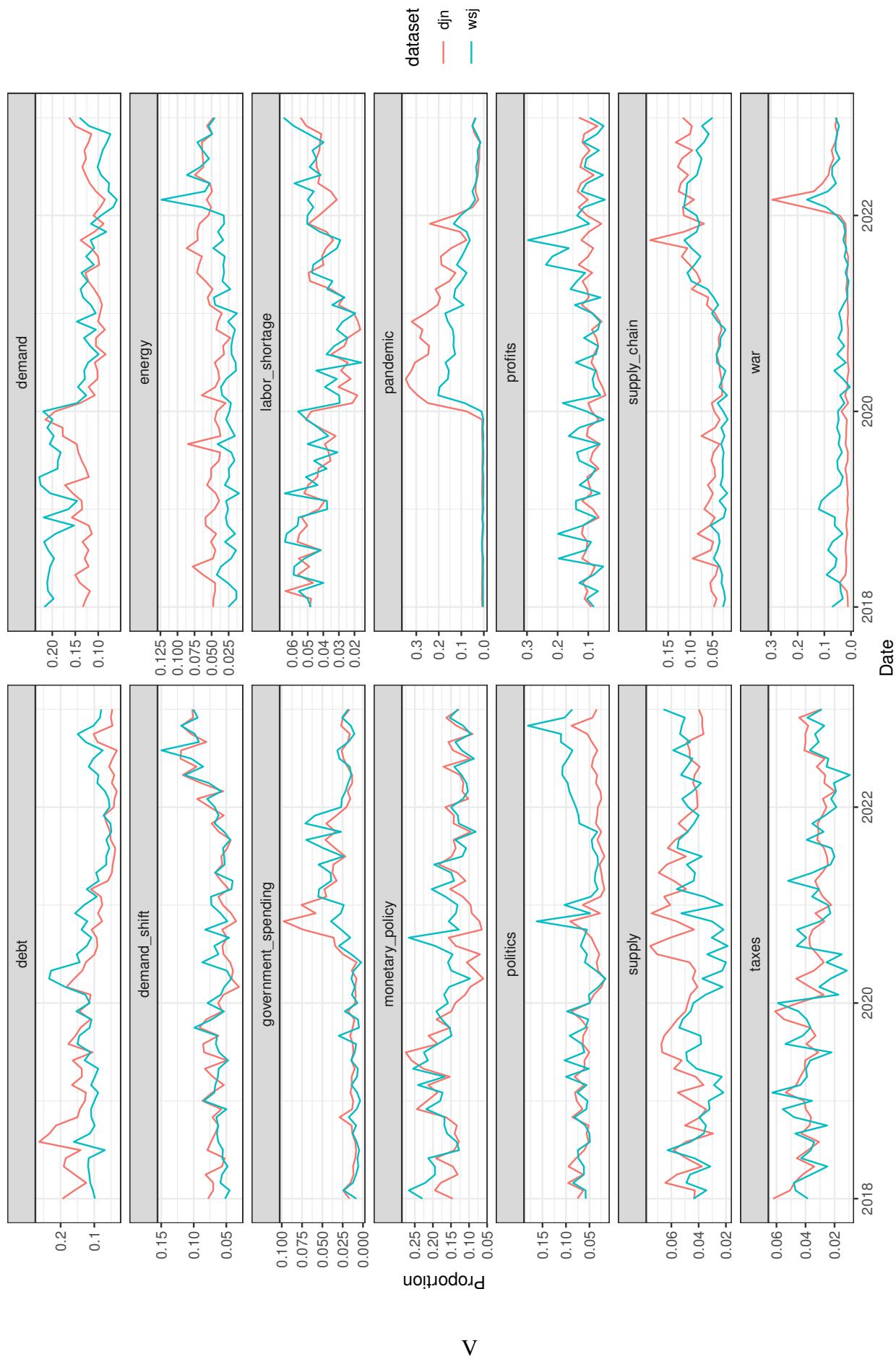
Note: The figure visualizes α , the prior for the document-topic distribution. We let the dynamic keyATM vary α across 4 latent states.

Figure A.F.5: Change of mean proportions



Note: The Figure shows the change in mean proportions since 2021 with the 95% confidence intervals. To calculate the relative proportions only the topics with pre-specified keywords were considered, so that the sum of the proportions of all keyword topics equals 1. All other non-keyword topics were excluded. We organized the topics by following the code system provided by Andre et al. (2023).

Figure A.F.6: Change of mean proportions



The figure shows the development of the smoothed proportions for both considered corpora. To calculate the relative proportions only the topics with pre-specified keywords were considered.

Table A.T.1: Elliott, Rothenberg and Stock unit root test results (Elliott et al., 1992)

Variable	Statistic	Critical Value 1%	Critical Value 5%	Critical Value 10%
Government Spending	1.6	1.95	3.11	4.17
Monetary Policy	5.22	1.95	3.11	4.17
Demand	3.73	1.95	3.11	4.17
Demand Shift	5.3	1.95	3.11	4.17
Supply Chain	4.3	1.95	3.11	4.17
Energy	2.17	1.95	3.11	4.17
Labor Shortage	9.01	1.95	3.11	4.17
Supply	3.44	1.95	3.11	4.17
Pandemic	2.03	1.95	3.11	4.17
Politics	4.85	1.95	3.11	4.17
War	0.83	1.95	3.11	4.17
Debt	4.72	1.95	3.11	4.17
Taxes	3.09	1.95	3.11	4.17
Profits	6.34	1.95	3.11	4.17

Table A.T.2: Narrative → Expectations Granger causality (level)

Narratives	One-Year Expectations (Pr(>F))	Three-Year Expectations (Pr(>F))
Demand		
Government Spending	0.23	0.38
Monetary Policy	0.68	0.01 **
Demand Shift	0.02 **	<0.01 ***
Demand (residual)	0.31	0.13
Supply		
Supply Chain	<0.01 ***	0.03 **
Energy	0.83	0.26
Labor Shortage	0.15	0.12
Supply (residual)	0.18	<0.01 ***
Miscellaneous		
Pandemic	0.76	0.94
Politics	0.15	0.10 *
War	0.76	0.24
Debt	0.79	0.07 *
Taxes	0.56	0.50
Profits	<0.01 ***	<0.01 ***
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01

Table A.T.3: Narrative → Expectations Granger causality (differences)

Narratives	One-Year Expectations (Pr(>F))	Three-Year Expectations (Pr(>F))
Demand		
Government Spending	0.13	0.07 *
Monetary Policy	0.55	0.29
Demand Shift	0.07 *	0.27
Miscellaneous		
Demand (residual)	0.80	0.84
Supply (residual)	0.22	0.12
Pandemic	0.68	0.65
Politics	0.67	0.98
War	0.50	0.12
Debt	0.03 **	0.88
Taxes	0.71	0.35
Profits	0.06 *	0.08 *
Supply		
Supply Chain	0.02 **	0.24
Energy	0.91	0.35
Labor Shortage	0.16	0.73
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01	

Table A.T.4: Income: Narrative → Expectations Granger causality (bHP-Filter)

	Narratives	1-Year Low Income	3-Year Low Income	1-Year Mid Income	3-Year Mid Income	1-Year High Income	3-Year High Income
Demand							
Government Spending	0.17	0.13	0.26	0.03 **	0.65	0.10	
Monetary Policy	0.84	0.74	0.42	0.03 **	0.23	0.27	
Demand Shift	0.05 *	0.86	0.17	0.34	0.02 **	0.01 **	
Demand (residual)	0.82	0.41	0.68	0.91	0.57	0.63	
Supply							
Supply Chain	<0.01 ***	0.16	0.02 **	0.83	0.02 **	0.07 *	
Energy	0.25	0.06 *	0.76	0.68	0.95	0.55	
Labor Shortage	0.06 *	0.21	0.01 **	0.99	0.02 **	0.69	
Supply (residual)	0.09 *	0.32	0.58	0.07 *	0.04 **	0.03 ***	
Miscellaneous							
Pandemic	0.40	0.56	0.13	0.24	0.20	0.05 *	
Politics	0.36	0.54	0.60	0.83	0.52	0.18	
War	<0.01 ***	0.12	0.02 **	0.49	0.09 *	0.20	
Debt	0.39	0.47	0.22	0.85	0.11	0.35	
Taxes	0.35	0.96	0.99	0.85	0.70	0.83	
Profits	<0.01 ***	0.02 **	<0.01 ***	0.22	0.06 *	<0.01 ***	

Note:

*p<0.1; **p<0.05; ***p<0.01

Table A.T.5: Education: Narrative → Expectations Granger causality (bHP-Filter)

	Narratives	1-Year Low Education	3-Year Low Education	1-Year Mid Education	3-Year Mid Education	1-Year High Education	3-Year High Education
Demand							
Government Spending	0.01 **	<0.01 ***	0.74	<0.01 ***	0.37	0.08 *	
Monetary Policy	0.16	0.57	0.71	0.29	0.52	0.65	
Demand Shift	<0.01 ***	0.63	0.48	0.77	0.01 **	<0.01 ***	
Demand (residual)	0.22	0.29	0.72	0.45	0.49	0.87	
Supply							
Supply Chain	<0.01 ***	0.50	0.10 *	0.08 *	<0.01 ***	0.01 **	
Energy	0.43	0.62	0.08 *	0.06 *	0.28	0.10 *	
Labor Shortage	0.10 *	0.80	0.02 **	0.84	0.24	0.61	
Supply (residual)	0.04 ***	0.58	0.45	0.38	0.02 **	0.03 **	
Miscellaneous							
Pandemic	0.14	0.94	0.17	0.90	0.25	0.15	
Politics	0.13	0.93	0.61	0.21	0.40	0.25	
War	<0.01 ***	0.66	<0.01 ***	0.04 **	0.19	0.04 **	
Debt	0.68	0.39	0.31	0.44	0.28	0.12	
Taxes	0.28	0.71	0.75	0.53	0.94	0.87	
Profits	<0.01 ***	0.14	0.08 *	0.05 *	0.02 **	<0.01 ***	
<i>Note:</i>							
* p<0.1; ** p<0.05; *** p<0.01							

X

Table A.T.6: Age: Narrative → Expectations Granger causality (bHP-Filter)

Narratives	1-Year Low Age	3-Year Low Age	1-Year Mid Age	3-Year Mid Age	1-Year High Age	3-Year High Age
Demand						
Government Spending	0.95	0.02 **	0.11	<0.01 ***	0.33	0.02 **
Monetary Policy	0.61	0.74	0.59	0.73	0.47	0.10
Demand Shift	0.17	0.11	0.14	0.07 *	0.06 *	0.92
Demand (residual)	0.34	0.56	0.25	0.93	0.75	0.10
Supply						
Supply Chain	0.01 ***	0.03 **	<0.01 ***	<0.01 ***	0.02 **	0.10 *
Energy	0.94	0.07 *	0.06 *	0.41	0.82	0.16
Labor Shortage	0.54	0.80	0.09 *	0.70	0.03 **	0.31
Supply (residual)	0.72	0.36	0.36	0.70	0.05 *	0.24
Miscellaneous						
Pandemic	0.14	0.14	0.84	0.26	0.28	0.72
Politics	0.59	0.50	0.24	0.61	0.25	0.59
War	0.01 **	<0.01 ***	0.10 *	0.10	0.03 **	0.62
Debt	0.04 **	0.96	0.69	0.52	0.25	0.79
Taxes	0.93	0.36	0.78	0.30	0.48	0.49
Profits	0.02 **	<0.01 ***	0.02 **	<0.01 ***	0.03 **	0.03 **
<i>Note:</i>						
* p<0.1; ** p<0.05; *** p<0.01						

Table A.T.7: Numeracy: Narrative → Expectations Granger causality (bHP-Filter)

	Narratives	1-Year Low Numeracy	3-Year Low Numeracy	1-Year High Numeracy	3-Year High Numeracy
Demand					
Government Spending	0.51	0.07 *	0.24	0.06 *	
Monetary Policy	0.39	0.40	0.39	0.46	
Demand Shift	0.39	0.70	0.15	0.61	
Demand (residual)	0.43	0.55	0.38	0.36	
Supply					
Supply Chain	0.01 **	0.53	<0.01 ***	0.54	
Energy	0.36	0.15	0.84	0.14	
Labor Shortage	0.07 *	0.96	<0.01 ***	0.95	
Supply (residual)	0.98	0.59	0.19	0.58	
Miscellaneous					
Pandemic	0.14	0.67	0.29	0.99	
Politics	0.69	0.22	0.36	0.24	
War	<0.01 ***	0.02 **	0.05 **	0.06 *	
Debt	0.25	0.19	0.11	0.15	
Taxes	0.18	0.44	0.99	0.40	
Profits	0.06 *	0.04 **	0.03 **	0.04 **	

Note:

* p<0.1; ** p<0.05; *** p<0.01

Figure A.F.7: Demand narratives' impulse responses (bHP)

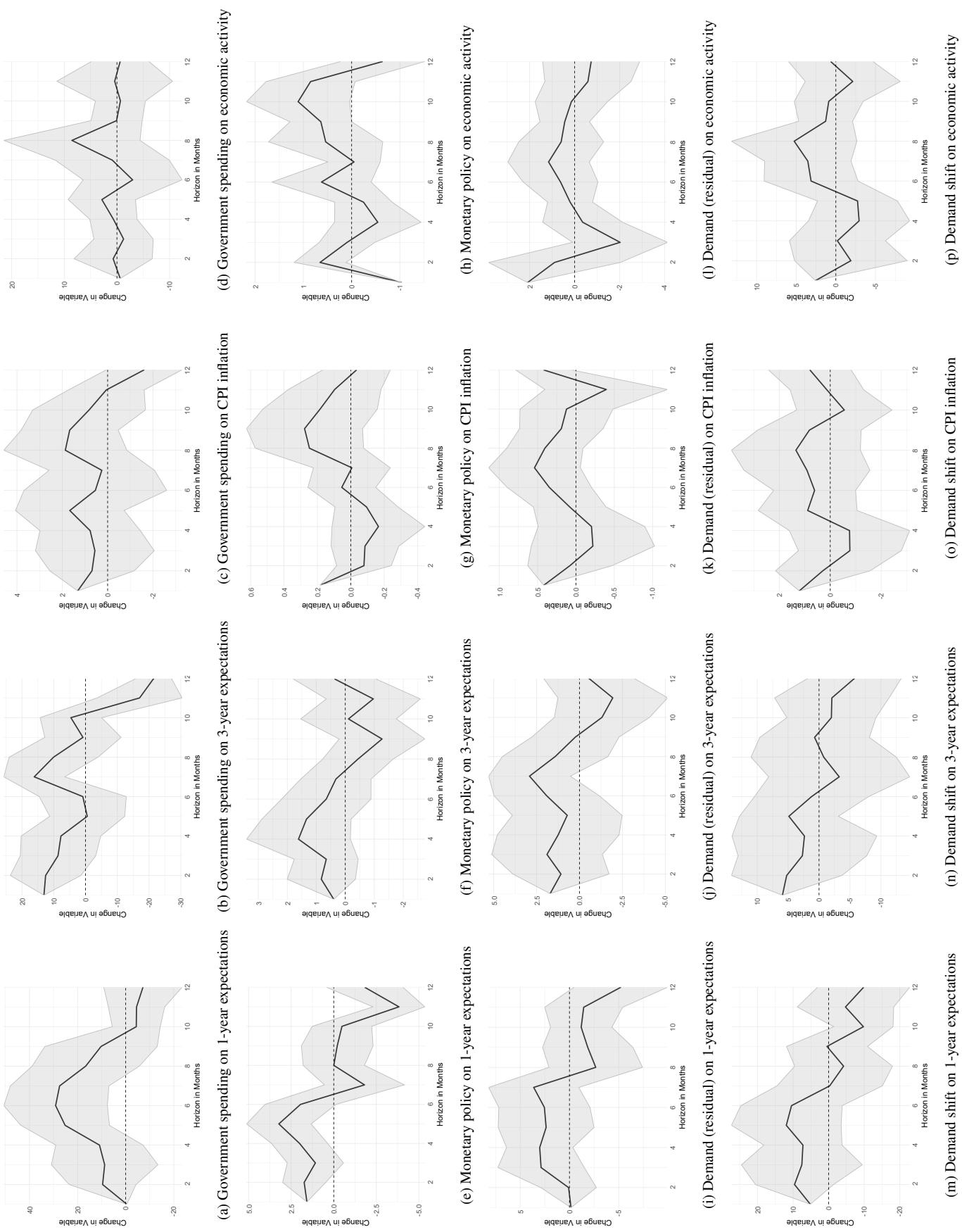


Figure A.F.8: Supply narratives' impulse responses (bHP)

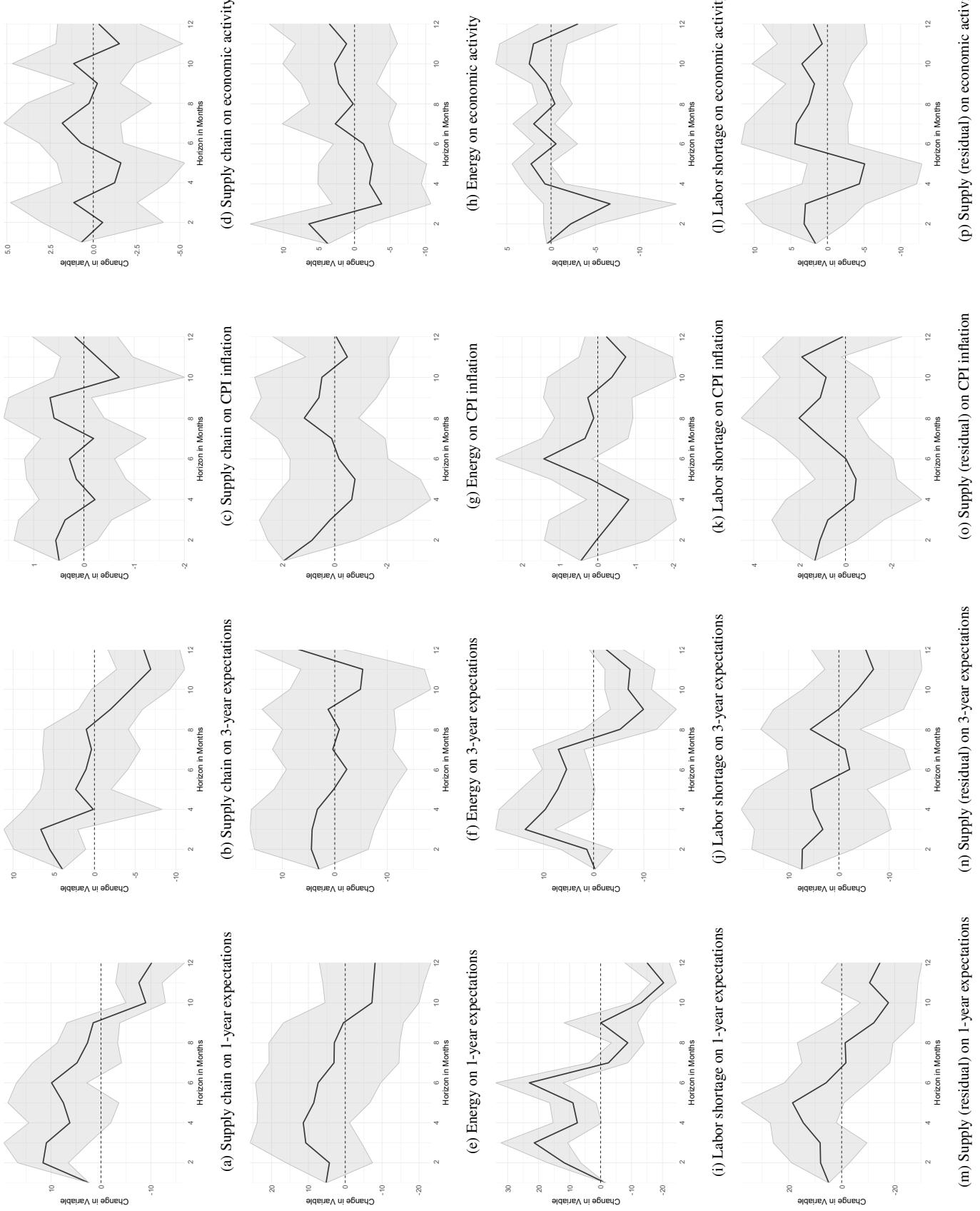


Figure A.F.9: Miscellaneous narratives' impulse responses (bHP)

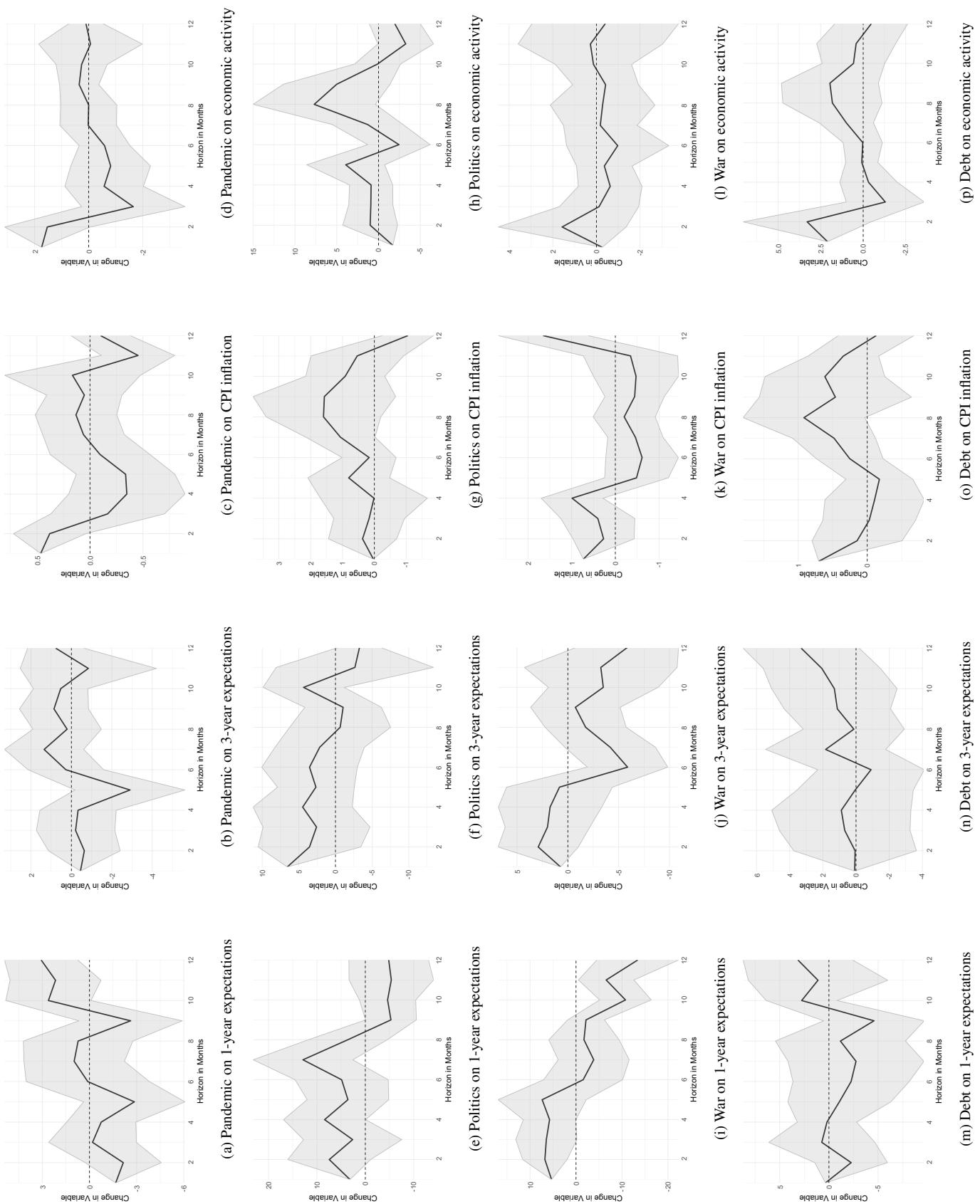


Figure A.F.10: Miscellaneous narratives' impulse responses (bHP)

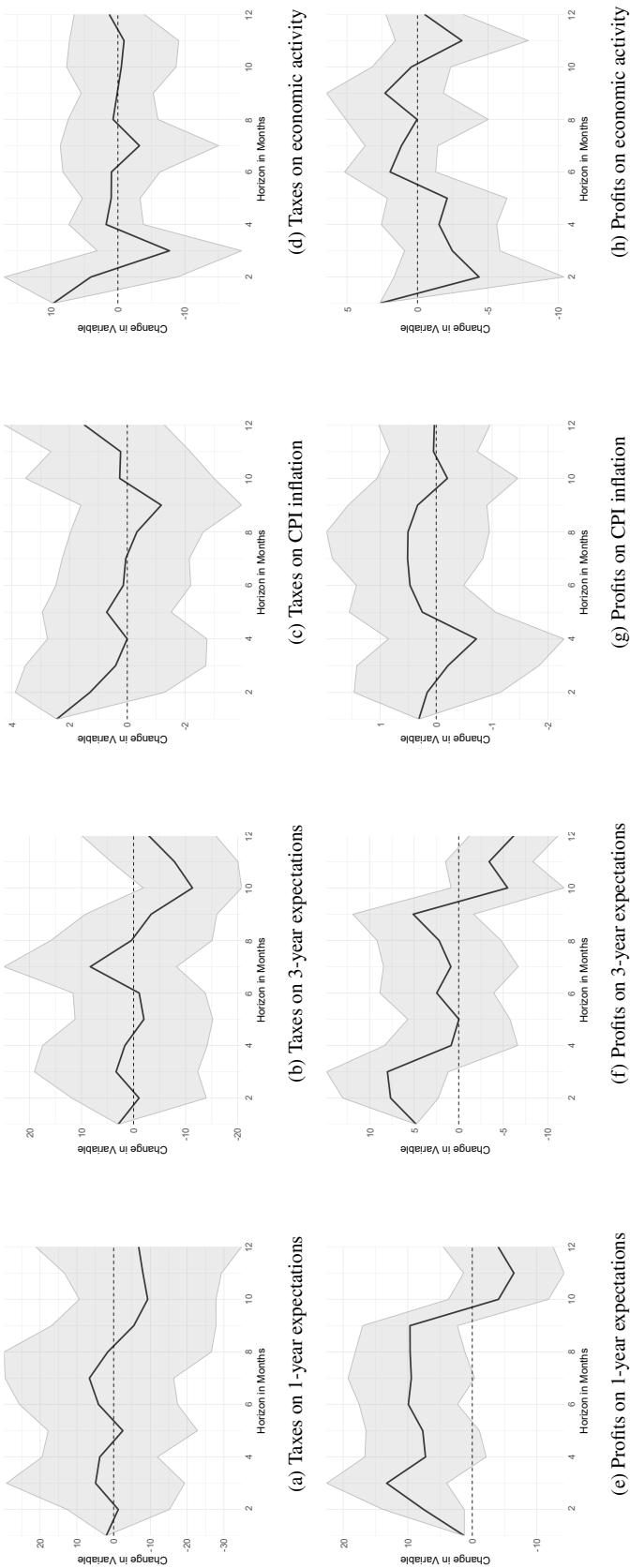
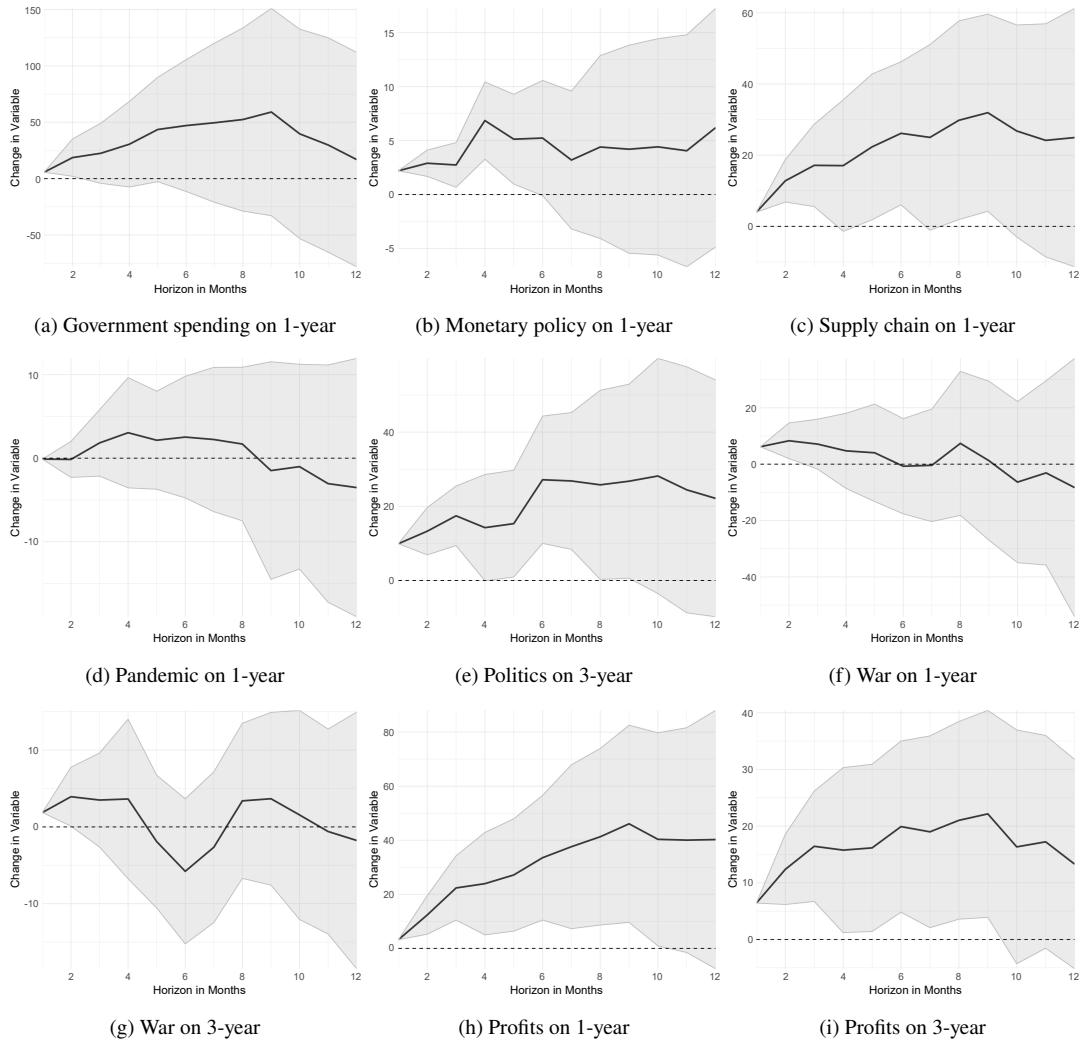
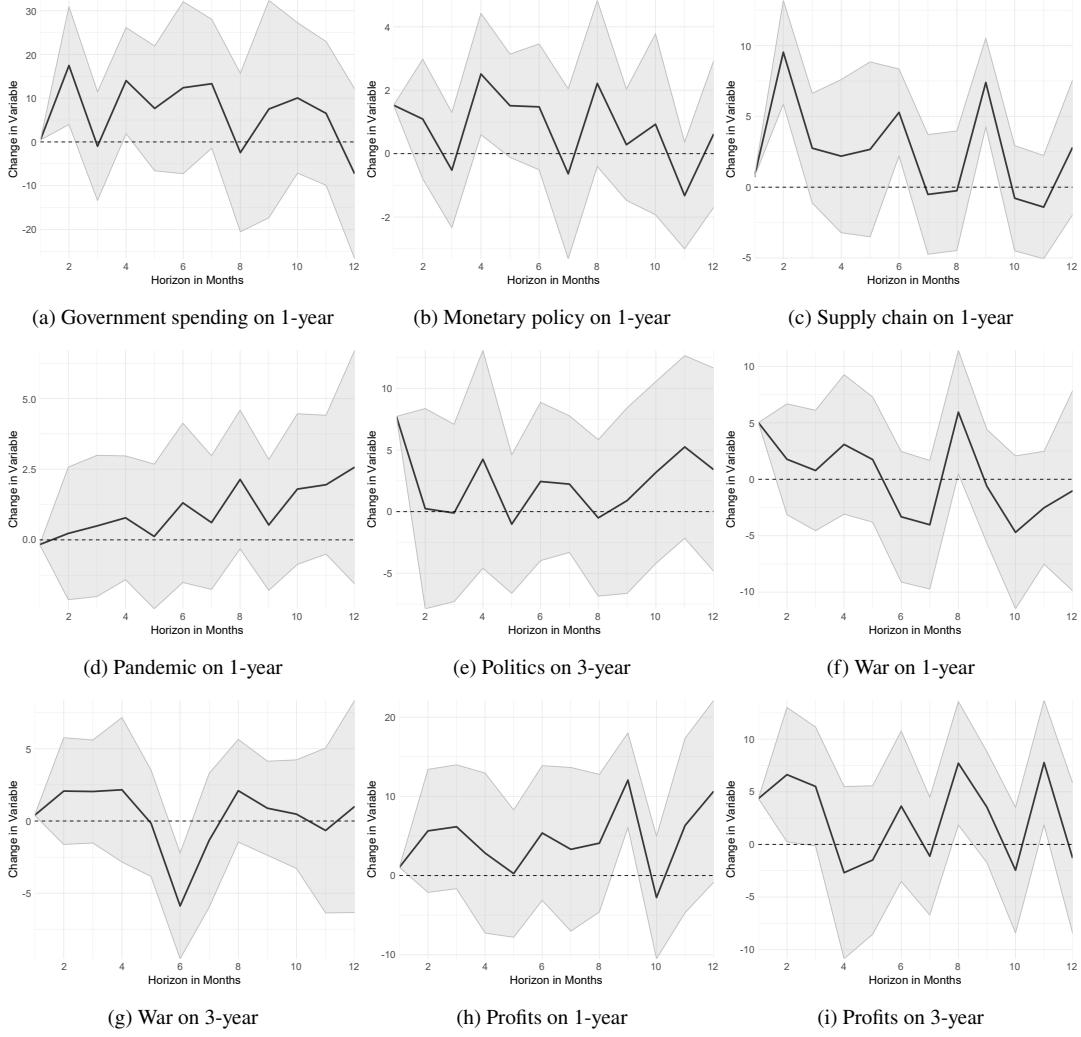


Figure A.F.11: Selection of narratives' impulse responses (level)



Note: The graphs show the mean responses and 90% confidence bands. The x-axis shows months (s) after narrative diffusion event; $t = 0$ is the month of the shock event. The y-axis shows the change in expectations as a response to the shock event. The shock considered is of the size of one standard deviation..

Figure A.F.12: Selection of narratives' impulse responses (differences)



Note: The graphs show the mean responses and 90% confidence bands. The x-axis shows months (s) after narrative diffusion event; $t = 0$ is the month of the shock event. The y-axis shows the change in expectations as a response to the shock event. The shock considered is of the size of one standard deviation.

A.2 Data preprocessing

In this section we describe the data pre-processing steps prior to the key ATM estimation. The Dow Jones Newswire is stored in .nml data files, that contain Extensible Markup Language (XML) Files. The raw Dow Jones Newswire contains roughly eight million documents for the observation period. This amount of documents and terms alone makes it computationally challenging. Moreover, many of these documents may not be of interest for the underlying research question(s) of this paper. To shrink the data set and at the same time allows for a greater focus on economic news about inflation, we pre-filtered the raw corpus in two ways: first, by using the subject codes from Dow Jones Newswire, we only selected relevant news sources, see [A.T.8](#). This left us with approximately 350,000 documents. Additionally we explicitly removed

articles that report tables, calendars, technical reports or press releases. Second, by applying a simple keyword filtering to generate a dataset only containing documents, which, in some way, report on inflation. The selected keywords are: "inflation", "deflation", "rising price[s]", "increasing price[s]", "price increase", "rise of prices" and "stagflation". The final corpus includes 163030 documents.

Table A.T.8: Selected News Sources

Subject Code	Description
DJIB	Dow Jones Investment Banker
DJG	Dow Jones Institutional News
GPRW	Dow Jones Global Press Release Wire
DJAN	Dow Jones Australian/New Zealand Report
AWSJ	Wall Street Journal Asia
WSJE	Wall Street Journal Europe
PREL	Press Release Wires
NRG	Dow Jones Energy Service
DJBN	Dow Jones Global News Select
AWP	AWP News
BRNS	Barron's
JNL	Wall Street Journal - Online Versions of Print Articles
WAL	Wall Street Journal (domestic) stories filed direct to Newswires
WLS	Wall Street Journal (all) on Newswires
WSJ	The Wall Street Journal - PB

As customary when using text-as-data methods, we reduce the dimensionality of the dataset according to Grimmer et al. (2022). Therefore, we first proceeded with an lemmatization. By lemmatization we mean a mapping process from words to lemmas, whereby a lemma is the canonical form of a set of by inflection related words (Grimmer et al., 2022). Accordingly, we used the Python package spaCy (Honnibal and Montani, 2017). This was followed by removing all punctuation, numbers, symbols, separators and urls. After removing these characters, we filtered out stop words, i.e. common words which have little to none information relating an article's subject. Additionally, time marks were taken out, as well as corpus-specific terms, which are relatively frequent but contain no information about the subject of an article like "quot" or "newswires". Finally, very rare terms were removed, as we are not able to use those efficiently in our model.

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