Optimal Inflation and the Identification of the Phillips Curve*

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A. Appendix

*The views expressed herein are those of the authors and do not necessarily reflect the views of the Bank of England or the National Bureau of Economic Research.

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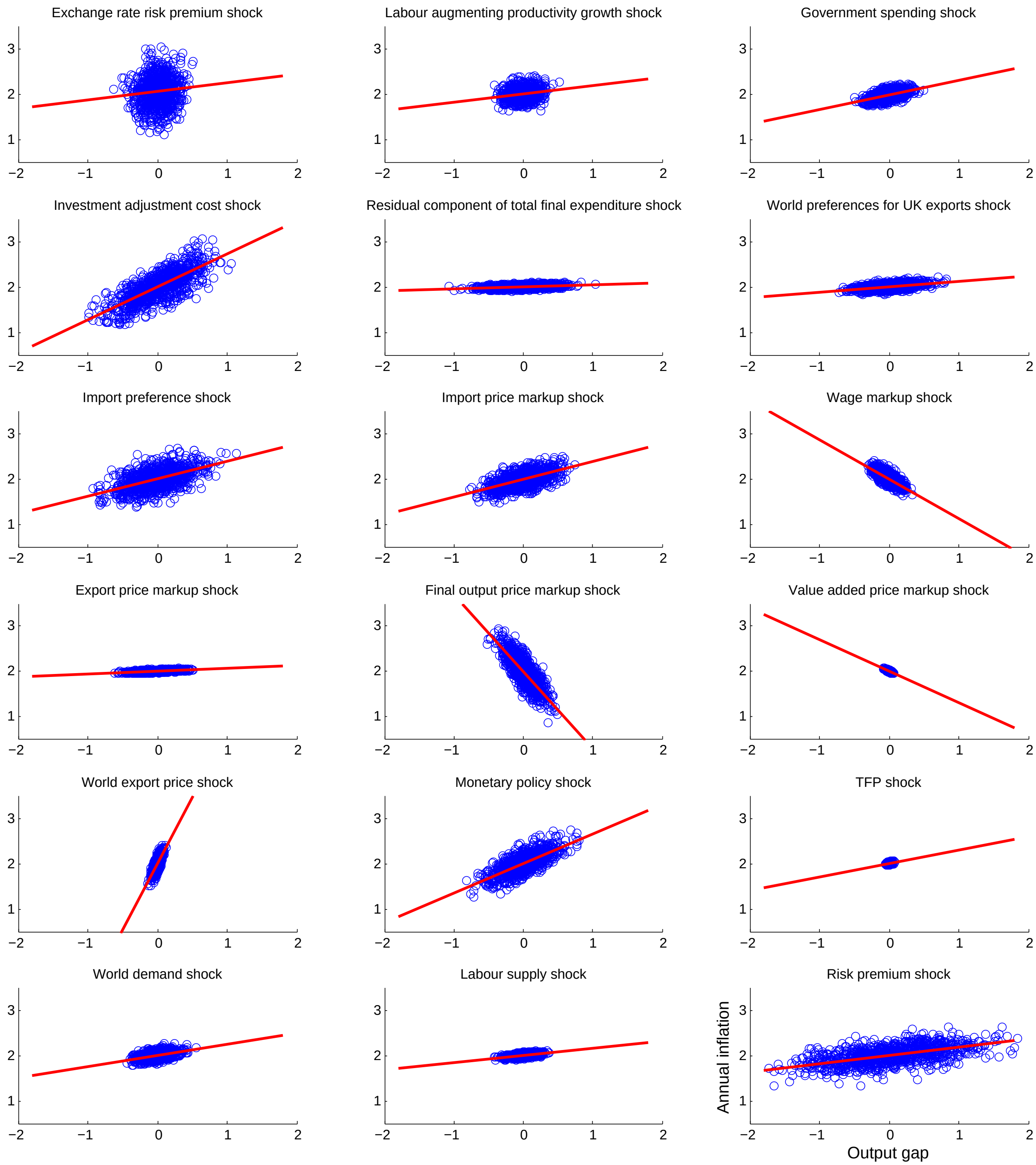
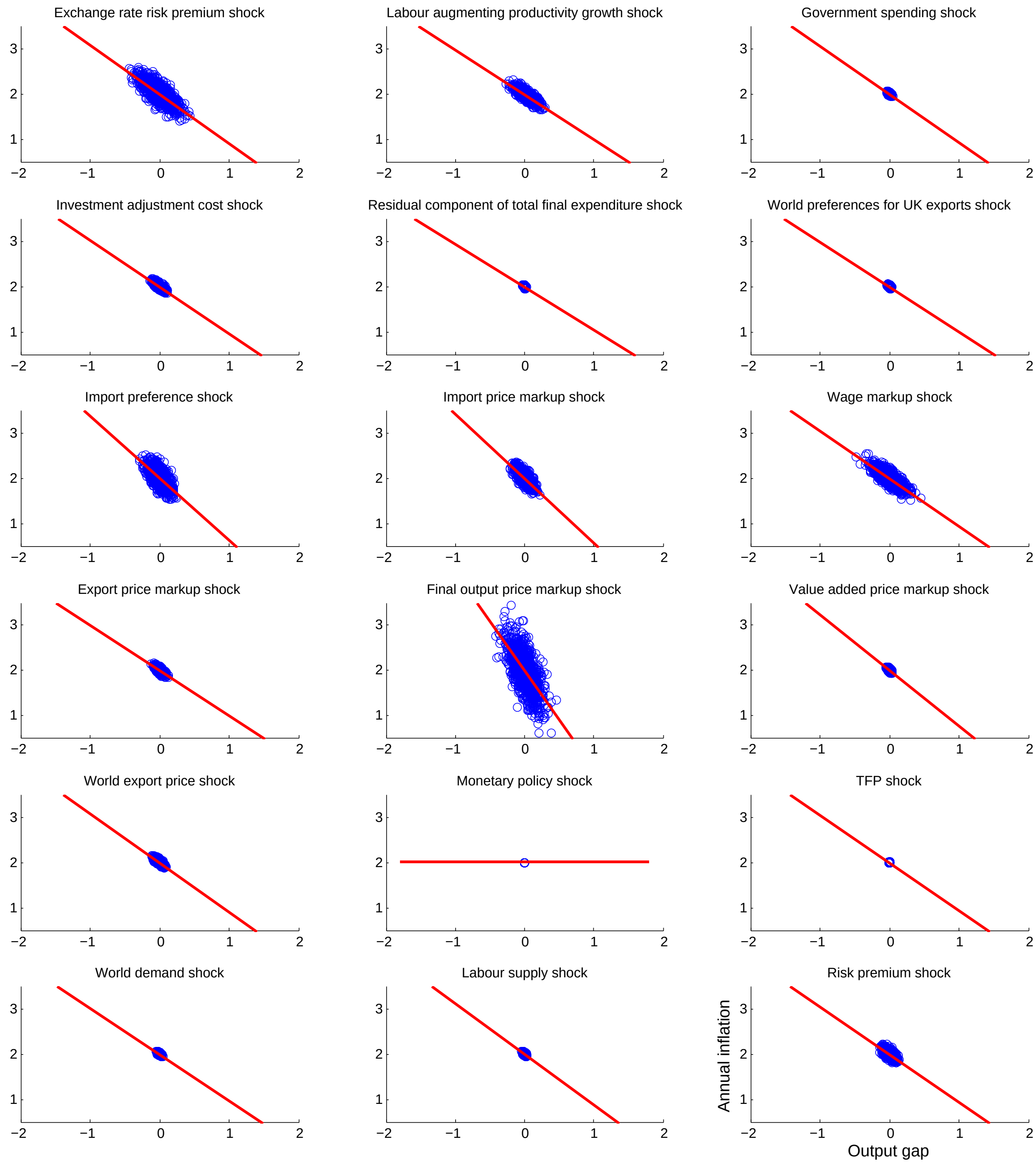
A.1. Additional large-scale DSGE model simulations.

Figure A1: *Inflation/output gap correlations by shock in a large-scale DSGE model with a Taylor rule*



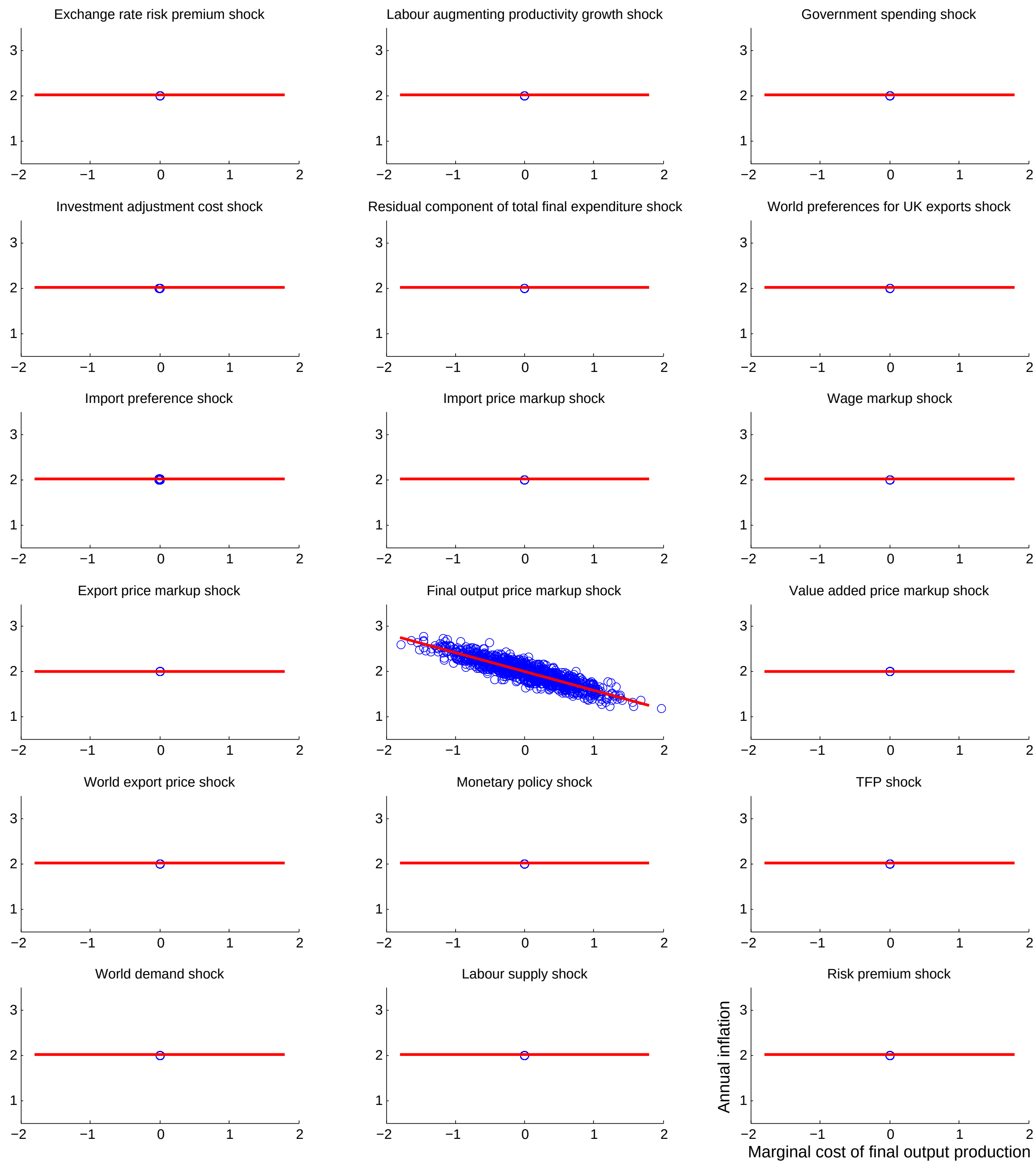
Notes: For each panel, 1000 periods of data are simulated from the model in Burgess et al. (2013) using the MAPS toolkit described in the same paper. For each panel, a realisation for the specified shock is drawn each period from a standard normal distribution. All other shocks are set to zero. The red lines show the lines of best fit from OLS regressions of the simulated annual inflation data on the (contemporaneous) flexible price output gaps. Monetary policy is specified using the estimated Taylor rule in the model.

Figure A2: *Inflation/output gap correlations by shock in a large-scale DSGE model under optimal discretionary policy*



Notes: For each panel, 1000 periods of data are simulated from the model in Burgess et al. (2013) using the MAPS toolkit described in the same paper. For each panel, a realisation for the specified shock is drawn each period from a standard normal distribution. All other shocks are set to zero. The red lines show the lines of best fit from OLS regressions of the simulated annual inflation data on the (contemporaneous) flexible price output gaps. Monetary policy is optimal policy under discretion, where the policymaker minimises, period by period, an ad hoc loss function containing the discounted sum of squared deviations of annual inflation from target (with a weight of 1) and the output gap (with a weight of 0.25). The solution is calculated using the algorithm of Dennis (2007).

Figure A3: *Inflation/output gap correlations by shock in a large-scale DSGE model under optimal discretionary policy (using real marginal costs as a policy target)*



Notes: For each panel, 1000 periods of data are simulated from the model in Burgess et al. (2013) using the MAPS toolkit described in the same paper. For each panel, a realisation for the specified shock is drawn each period from a standard normal distribution. All other shocks are set to zero. The red lines show the lines of best fit from OLS regressions of the simulated annual inflation data on the (contemporaneous) flexible price output gaps. Monetary policy is optimal policy under discretion, where the policymaker minimises, period by period, an ad hoc loss function containing the discounted sum of squared deviations of annual inflation from target (with a weight of 1) and the marginal cost of final output production (with a weight of 0.1). The solution is calculated using the algorithm of Dennis (2007).

A.2. List of metropolitan areas used in regional data estimation

We use 22 of the 23 areas for which CPI data is currently published by the BLS: Atlanta-Sandy Springs-Roswell, Baltimore-Columbia-Towson, Boston-Cambridge-Newton, Chicago-Naperville-Elgin, Dallas-Fort Worth-Arlington, Denver-Aurora-Lakewood, Detroit-Warren-Dearborn, Houston-The Woodlands-Sugar Land, Los Angeles-Long Beach-Anaheim, Miami-Fort Lauderdale-West Palm Beach, Minneapolis-St Paul-Bloomington, New York-Newark-Jersey City, Philadelphia-Camden-Wilmington, Phoenix-Mesa-Scottsdale, San Diego-Carlsbad, San Francisco-Oakland-Hayward, Seattle-Tacoma-Bellevue, St Louis, Tampa-St Petersburg-Clearwater, Urban Alaska, Urban Hawaii and Washington-Arlington-Alexandria. We exclude Riverside-San Bernardino-Ontario, for which data are only published from 2018 onwards. In order to maximise the size of our cross-sectional sample, we also add the six previously published metropolitan areas for which CPI data was discontinued after 2017: Cincinnati-Hamilton, Cleveland-Akron, Kansas City, Milwaukee-Racine, Pittsburgh and Portland-Salem. The earlier conference draft of this paper used a smaller sample of only 23 areas. Moving to the full set yields almost identical results. Since 2018, the BLS has published separate CPI backdata for Washington and Baltimore (although based on a much smaller sample), which were previously only available combined. We opt to split them given the quite different behaviour of the data in the two areas

A.3. Regional Phillips curves using alternative CPI measures

Table A1 explores the robustness of our main results to using different measures of the CPI. If regional supply shocks affecting food and energy prices were important, we would expect to see a steeper Phillips curve slope for core CPI inflation than for headline CPI inflation. Similarly, since services are typically less tradeable than goods, services CPI inflation should also be relatively less affected by regional supply shocks. Comparing the first three columns, estimates of the Phillips curve slope are similar at around -0.4 for headline, core and services CPI inflation.

Interestingly, it appears that over our full sample, housing rents are playing an important role in driving the services Phillips curve, as highlighted recently by Daly (2019). The fourth column shows that excluding shelter, the slope declines and becomes insignificant. This suggests that the mechanism we are uncovering may not be a simple story of inflation being driven by real marginal labour costs, since the production of housing services contain little labour input. The importance of rents appears to be partly due to the influence of the financial crisis, however. Restricting the sample to the pre-crisis period in the final column, we recover a significant slope coefficient of -0.19, compared to a *positive* coefficient in the specification without year fixed effects in column five.

Table A1: *US Metro area Phillips curve, different CPI measures*

	(1)	(2)	(3)	(4)	(5)	(6)
Inflation variable	CPI	Core CPI	Serv. CPI	Serv. CPI ex. shelter	Serv. CPI ex. shelter	Serv. CPI ex. shelter
Sample	1990-2017	1990-2017	1990-2017	1990-2017	1990-2007	1990-2007
Unemployment rate	-0.394***	-0.379***	-0.445***	-0.111	0.119*	-0.187**
	[0.066]	[0.052]	[0.063]	[0.080]	[0.061]	[0.090]
Inflation expectations	1.948***	0.225	0.828***	2.000***	1.596***	2.590***
	[0.142]	[0.141]	[0.189]	[0.306]	[0.160]	[0.445]
Inflation						
First lag	-0.214***	0.105***	0.156***	-0.043	0.089*	0.019
	[0.040]	[0.034]	[0.041]	[0.032]	[0.048]	[0.046]
Observations	1,525	1,525	1,525	1,525	965	965
R-squared	0.547	0.487	0.481	0.406	0.326	0.412
Metro area FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No	Yes
Seasonal dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Specification for regressions (1), (2), (3), (4) and (6) is the same as Specification (4) in Table 3 in the main text with dependent variables and samples as described in the table. Specification for regression (5) is the same as Specification (2) in Table 3 in the main text, with dependent variable and sample as described in the table.

References

Burgess, Stephen, Emilio Fernandez-Corugedo, Charlotta Groth, Richard Harrison, Francesca Monti, Konstantinos Theodoridis, and Matt Waldron. 2013. "The Bank of England's forecasting platform: COMPASS, MAPS, EASE and the suite of models." Bank of England Working Paper 471.

Daly, Mary. 2019. "Discussion of 'Prospects for Inflation in a High Pressure Economy' by Peter Hooper, Frederic S. Mishkin and Amir Sufi." Presentation given at the 2019 US Monetary Policy Forum. https://www.frbsf.org/our-district/files/MD-Presentation-USMPF-February-21-2019-Final.pdf.

Dennis, Richard. 2007. "Optimal Policy in Rational Expectations Models: New Solution Algorithms." *Macroeconomic Dynamics*, 11(1): 31–55.