

On the robustness of commonly employed  
empirical methods in estimating  
the exchange rate pass-through

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# Introduction

- ▶ *Exchange rate pass-through*: degree to which exchange rate changes are reflected in prices of traded goods (Menon, 1995)
- ▶ The degree of pass-through has important implications for
  - ▶ the stabilisation benefits of flexible exchange rates
  - ▶ the transmission of international business cycles
  - ▶ optimal monetary policy in open economies
- ▶ Pass-through issues central in recent 'New Open Economy Macroeconomics' (NOEM) literature
- ▶ Large literature estimating the exchange rate pass-through

# Introduction

Commonly employed methods in applied macroeconometrics:

## 1. Data-based approaches

- ▶ Conditional single-equation models ('pass-through regressions')
- ▶ Structural vector autoregressions (VARs)

## 2. Theory-based approaches

- ▶ GMM estimation of individual equations
- ▶ Impulse response matching
- ▶ Maximum likelihood (FIML) estimation of fully specified models

# Introduction

- ▶ Pertinent question: how robust are these methods in estimating the exchange rate pass-through?
- ▶ Approach taken in this lecture:
  - ▶ Write down a theoretical model of import prices
  - ▶ Ask under what circumstances each method recovers the 'true' degree of pass-through
- ▶ Focus on problems related to
  - ▶ identification of shocks and parameters
  - ▶ the specification of the time-series properties of the data
  - ▶ small sample estimation bias

# Structure of talk

1. A NOEM type import price equation
2. Data-based approaches
3. Theory-based approaches
4. Concluding remarks

# A NOEM type import price equation

## Assumptions

- ▶ Foreign firm produces differentiated good for sale in domestic market
- ▶ International goods markets are segmented
- ▶ Firm allowed to change price with a fixed probability  $(1 - \eta)$  in each period (Calvo, 1983)
- ▶ Prices set in importing country's currency (local currency pricing)
- ▶ Optimal frictionless price:  $p_t^m = s_t + mc_t^f$

# A NOEM type import price equation

## Model

- ▶ Log-linearised import price equation

$$\Delta p_t^m = \beta E_t \Delta p_{t+1}^m - \frac{(1 - \beta\eta)(1 - \eta)}{\eta} (p_t^m - s_t - mc_t^f) + \varepsilon_{p,t}$$

where  $\beta \in [0, 1]$  is discount factor,  $\varepsilon_{p,t}$  is white noise

- ▶ Models for exchange rate and marginal costs

$$\begin{aligned}\Delta s_t &= \gamma_s \Delta s_{t-1} + \varepsilon_{s,t} \\ \Delta mc_t^f &= \gamma_{mc} \Delta mc_{t-1}^f + \varepsilon_{mc,t}\end{aligned}$$

- ▶ Exchange rate pass-through: impulse response of import price to an exchange rate shock  $\varepsilon_{s,t}$

# A NOEM type import price equation

## Calibration

- ▶ Parameters in import price equation:  $\beta = 0.99, \eta = 0.75$
- ▶ Parameters in completing models:  $\gamma_s = 0, \gamma_{mc} = 0.8$
- ▶ Standard deviations of shocks:
  - ▶  $\sigma_s = 0.032$  (Exchange rate shock)
  - ▶  $\sigma_p = 0.022$  (Import price shock)
  - ▶  $\sigma_{mc} = 0.005$  (Marginal cost shock)

# Data-based approaches

## Pass-through regression

- ▶ Pass-through regression

$$\Delta p_t^m = \sum_{i=0}^p a_i \Delta s_{t-i} + \sum_{i=0}^p b_i \Delta mc_{t-i}^f + \sum_{i=1}^p c_i \Delta p_{t-i}^m + \rho \left( p_{t-1}^m - \lambda_1 s_{t-1} - \lambda_2 mc_{t-1}^f \right) + u_{p,t}$$

- ▶ Exchange rate pass-through: accumulated response of import price to exchange rate change

# Data-based approaches

Mapping from theoretical model to pass-through regression

- ▶ Does the pass-through regression recover the 'true' exchange rate pass-through? YES!
- ▶ The closed form solution of the theoretical model is

$$\Delta p_t^m = \phi_1 \Delta s_t + \phi_2 \Delta mc_t^f - \phi_3 (p^m - s - mc^f)_{t-1} + \tilde{u}_{p,t}$$

where

$$\phi_1 = \frac{1 - \eta}{1 - \gamma_s \beta \eta}, \quad \phi_2 = \frac{1 - \eta}{1 - \gamma_{mc} \beta \eta}, \quad \phi_3 = 1 - \eta$$

- ▶ Pass-through depends on import price equation  $(\beta, \eta)$  and exchange rate process  $(\gamma_s)$

# Data-based approaches

Structural vector autoregressions (VARs)

- ▶ General VAR specification

$$y_t = \sum_{i=1}^p A_i y_{t-i} + u_t, \quad u_t = B\varepsilon_t, \quad E[u_t u_t'] = BB' = \Omega$$

$$y_t' = [s_t, mc_t^f, p_t^m]$$

$$u_t' = [u_{s,t}, u_{mc,t}, u_{p,t}]$$

- ▶ Exchange rate pass-through: impulse response of prices to an exogenous 'exchange rate shock'

# Data-based approaches

## Structural vector autoregressions (VARs)

- ▶ Common identification scheme: exchange rate first in recursive ordering

$$\begin{bmatrix} u_{s,t} \\ u_{mc,t} \\ u_{p,t} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 \\ b_{21} & b_{22} & 0 \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{mc,t} \\ \varepsilon_{p,t} \end{bmatrix}$$

- ▶ Justification: (Choudhri et al., 2005)
  - ▶ publication lags in official trade statistics
  - ⇒ foreign exchange market observes import prices with at least a one period lag

# Data-based approaches

Mapping from theoretical model to structural VAR

- ▶ Does the structural VAR recover the 'true' exchange rate pass-through? YES!
- ▶ When  $\gamma_s = \gamma_{mc} = 0$ , the solution to the rational expectations model can be written as

$$\begin{bmatrix} s_t \\ mc_t^f \\ p_t^m \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 - \eta & 1 - \eta & \eta \end{bmatrix} \begin{bmatrix} s_{t-1} \\ mc_{t-1}^f \\ p_{t-1}^m \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 - \eta & 1 - \eta & \eta \end{bmatrix} \begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{mc,t} \\ \varepsilon_{p,t} \end{bmatrix}$$

# Data-based approaches

Mapping from theoretical model to structural VAR

- ▶ Key assumptions generating this result
  - ▶ Moving average (MA) representation for the variables in  $y_t$  is invertible
    - ⇒ VAR representation exists
  - ▶ All state variables in the theoretical model included in the VAR
    - ⇒ VAR is of finite order
  - ▶ Identification scheme is correct

# Data-based approaches

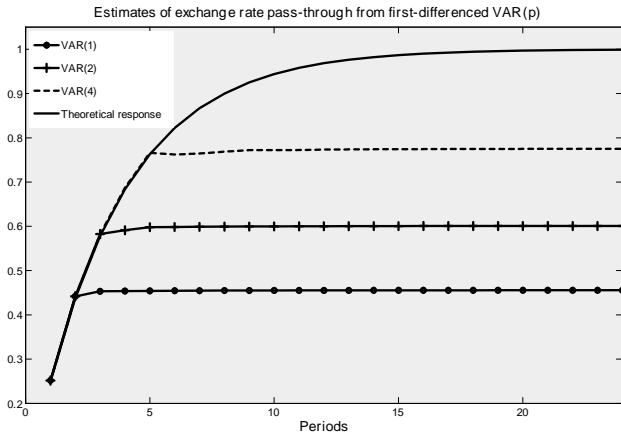
Potential source of bias: 'Overdifferencing'

- ▶ First-differenced models common in the pass-through literature  
(e.g., Campa & Goldberg, 2005; Choudhri et al., 2005)
- ▶ If  $y_t$  is non-stationary but cointegrated, estimating a VAR in  $\Delta y_t$  involves loss of information
- ▶ Technically: unit root in the MA representation for  $\Delta y_t$   
 $\implies$  no finite-order VAR can describe  $\Delta y_t$

# Data-based approaches

Potential source of bias: 'Overdifferencing'

- ▶ Simulation experiment:
  - ▶ Generate artificial data from theoretical model
  - ▶ Estimate first-differenced VARs for different lag-orders
  - ▶ Compute impulse response of import prices to exchange rate shock
- ▶ Note: identical results obtain for first-differenced pass-through regression



Note: Results based on population VAR responses ( $T = \infty$ )

# Data-based approaches

Potential source of bias: Mis-identification of exchange rate shock

- ▶ Common feature of open-economy models: exchange rates react instantly to news about variables that signal future monetary policy
- ▶ If exchange rates respond to import prices within period
  - ⇒ recursive identification scheme invalid
  - ⇒ bias in estimate of exchange rate pass-through
- ▶ Finding sensible identification restrictions in VAR models for open economies remains a challenge

# Theory-based approaches

## Generalised method of moments (GMM)

- ▶ Limited information method: does not require the econometrician to specify a model for the exchange rate or marginal costs
- ▶ Estimating equation

$$\Delta p_t^m = \beta \Delta p_{t+1}^m - \frac{(1 - \beta\eta)(1 - \eta)}{\eta} (p_t^m - s_t - mc_t^f) + \omega_t$$

where  $\omega_t = \varepsilon_{p,t} - \beta v_{t+1}$  and  $v_{t+1} \equiv \Delta p_{t+1}^m - E_t \Delta p_{t+1}^m$ .

# Theory-based approaches

## Generalised method of moments (GMM)

- ▶ Rational expectations assumption implies

$$E_t [\omega_t(\theta) z_t] = 0, \quad t = 1, \dots, T$$

where  $\theta = \{\beta, \eta\}$  and  $z_t$  satisfies  $E_t [\varepsilon_{p,t} z_t] = 0$ .

- ▶ GMM estimator

$$\hat{\theta}_{GMM} = \arg \min_{\theta} \left( \frac{1}{T} \sum_{t=1}^T \omega_t(\theta) z_t \right)' W_T \left( \frac{1}{T} \sum_{t=1}^T \omega_t(\theta) z_t \right)$$

where  $W_T$  is a positive definite weighting matrix

# Theory-based approaches

## Generalised method of moments (GMM)

- ▶ Potential source of bias: small sample estimation bias  
(e.g., Mavroeidis, 2005).
- ▶ Attributable to *weak identification*: instruments only weakly correlated with the endogenous variable(s)
- ▶ Quality of instruments depends on processes for the exchange rate and marginal costs
  - ▶ If  $\gamma_{mc} = \gamma_s = 0$ , parameters in import price equation not identified
  - ▶ Identification requires higher-order dynamics in one of the driving variables

# Theory-based approaches

## Generalised method of moments (GMM)

► Simulation experiment:

- Generate artificial data from theoretical model
- Estimate  $\beta$  and  $\eta$  using GMM
- Instruments

$$z_{1,t} = \left\{ \Delta s_t, \Delta mc_t^f, (p_{t-1}^m - s_{t-1} - mc_{t-1}^f) \right\}$$
$$z_{2,t} = \left\{ \begin{array}{l} \sum_{i=0}^4 \Delta s_{t-i}, \sum_{i=0}^4 \Delta mc_{t-i}^f, \\ (p_{t-1}^m - s_{t-1} - mc_{t-1}^f), \sum_{i=1}^4 \Delta p_{t-i}^m \end{array} \right\}$$

Small instrument set $z_{1,t}$						
	$T = 100$		$T = 1000$		$T = 10000$	
	<b>Med</b>	Med SE	<b>Med</b>	Med SE	<b>Med</b>	Med SE
$\beta$	<b>0.90</b>	0.657	<b>0.97</b>	0.188	<b>0.99</b>	0.060
$\eta$	<b>0.74</b>	0.071	<b>0.75</b>	0.022	<b>0.75</b>	0.007

Large instrument set $z_{2,t}$						
	$T = 100$		$T = 1000$		$T = 10000$	
	<b>Med</b>	Med SE	<b>Med</b>	Med SE	<b>Med</b>	Med SE
$\beta$	<b>0.30</b>	0.246	<b>0.85</b>	0.163	<b>0.97</b>	0.059
$\eta$	<b>0.76</b>	0.032	<b>0.75</b>	0.018	<b>0.75</b>	0.007

Note: Results based on 1000 simulations with  $\beta = 0.99$ ,  $\eta = 0.75$ ,  $\gamma_s = 0$ ,  $\gamma_{mc} = 0.8$ . Table reports the median point estimate and the median standard error across simulations.

# Theory-based approaches

## Impulse response matching

- ▶ Impulse response matching estimator: choose  $\theta$  to minimise distance between VAR impulse responses and model-based impulse responses

$$\hat{\theta}_{IRF} = \arg \min_{\theta} (irf_{VAR} - irf_{MOD}(\theta)) W_T (irf_{VAR} - irf_{MOD}(\theta))'$$

where  $W_T$  is a positive definite weighting matrix

- ▶ Smets & Wouters (2002) and Choudhri et al. (2005) estimate NOEM type import price equations by matching impulse responses of import prices to exchange rate shock

# Theory-based approaches

## Impulse response matching

- ▶ Potential source of bias: lack of identification  
(Canova & Sala, 2006)
- ▶ Recall: closed form solution of theoretical model

$$\Delta p_t^m = \frac{1 - \eta}{1 - \gamma_s \beta \eta} \Delta s_t + \frac{1 - \eta}{1 - \gamma_{mc} \beta \eta} \Delta mc_t^f - (1 - \eta) (p^m - s - mc^f)_{t-1} + \tilde{u}_{p,t}$$

- ▶ If  $\gamma_s = 0$ , exchange rate pass-through depends only on  $\eta$   
 $\implies \beta$  is not identified

# Theory-based approaches

## Impulse response matching

- ▶ Potential source of bias: VAR is misspecified
- ▶ Simulation experiments:
  - ▶ Generate datasets from economic model with  $T = 100$
  - ▶ Compute impulse responses from second-order VAR in *i*) levels and *ii*) first differences
  - ▶ Estimate  $\eta$  using impulse response matching

	Median estimate of $\eta$	
	VAR in levels	First differenced VAR
$T = 100$	0.73	0.92
Population VAR	0.75	0.94

Note: Results based on 1000 simulations of model with  $\beta = 0.99$  and  $\eta = 0.75$ . Weighting matrix is the inverse of the diagonal matrix containing the variances of the impulse responses computed using the bias-corrected bootstrap method of Kilian (1998)

# Theory-based approaches

Full information maximum likelihood (FIML)

- ▶ Full information method: requires a model for the exchange rate and marginal costs
- ▶ Estimation based on closed form solution  
⇒ exploits cross-restrictions implied by rational expectations assumption
- ▶ Assumes that the structural shocks are jointly normally distributed

# Theory-based approaches

## Full information maximum likelihood (FIML)

- ▶ If model is correctly specified:
  - ▶ FIML estimator more efficient than GMM estimator
  - ▶ Better small sample properties than GMM  
(e.g., Fuhrer and Rudebusch, 2004; Lindé, 2005)
- ▶ Simulation experiment with  $T = 100$ : median unbiased estimates of  $\beta$  and  $\eta$
- ▶ However: difficult to model the exchange rate  
 $\implies$  misspecification in exchange rate process may bias estimates of parameters in import price equation

# Concluding remarks

## Data-based methods

- ▶ potentially consistent with wide range of theoretical models of exchange rate pass-through
- ▶ estimates not robust to changes in monetary policy regime
- ▶ estimates sensitive to assumptions about the time-series properties of the data

## Theory-based methods

- ▶ provides information about 'deep' parameters determining the degree of pass-through
- ▶ problems related to misspecification and identification likely to be particularly severe in open-economy models