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Sources of exchange-rate volatility: Impulses or propagation?

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Abstract

This paper examines whether the remarkable increase in exchange-rate variability since the end of the Bretton Woods period has been the result of a less stable structure (the propagation mechanism) or more volatile shocks (the impulses). Using monthly data over the 1957:1 to 2000:12 period from the US, Canada, Germany, and the UK, our estimates of actual and counterfactual variances suggest that the increased volatility is entirely the result of more violent shocks, and not at all the consequence of a less stable structure. This result is robust to a number of different specifications examined.

JEL classification: F3; F4
Keywords: Exchange rates; VAR models

1. Introduction

One of the most striking developments in the behavior of exchange rates has been the tremendous increase in volatility that has followed the end of the Bretton Woods system in 1971 (see Fig. 1). While this is usually viewed as the inevitable consequence of floating, the question of why and how the new regime resulted in such an increase in exchange-rate variability still needs to be addressed. The goal of the present paper is to distinguish between two competing explanations: one that faults a supposedly less stable structure and one that holds responsible the shocks that originated in a more volatile environment.

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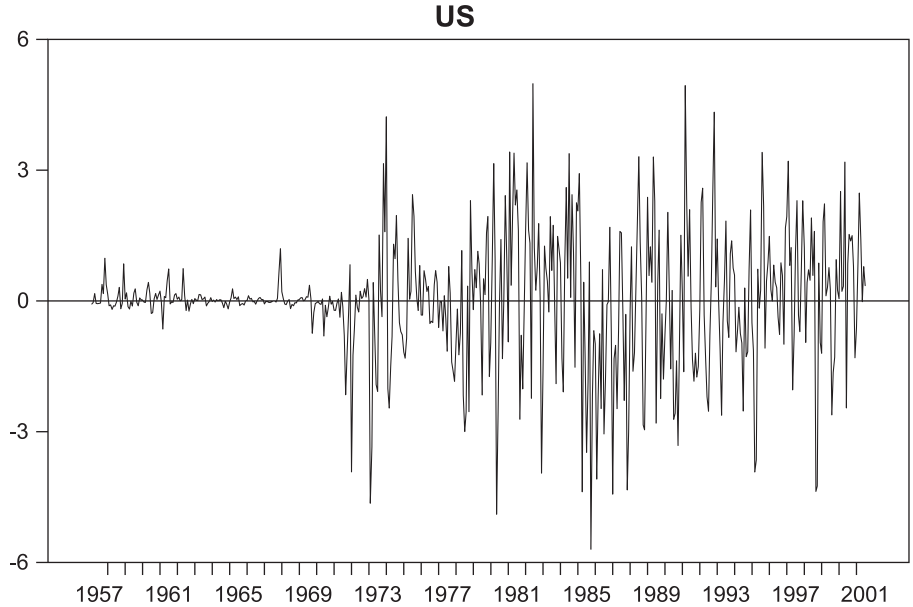

Fig. 1. Difference of the log monthly US nominal effective exchange rate.

Exchange-rate variability has been the subject of intense study, but has been usually considered as an exogenous factor, rather than something that itself needs to be explained. Thus, a vast literature has investigated whether the much greater post-Bretton Woods volatility has affected the behavior of key macroeconomic variables using various data sets and econometric methods. Overall, the evidence seems to suggest that there have been no such effects, or that they are too small to measure.[1] For example, Baxter and Stockman (1989) find that the exchange-rate regime does not influence the behavior of industrial production, consumption, exports, and imports for a sample of 49 countries. Using a very different methodology, Gagnon (1993) similarly reports that exchange-rate variability has an insignificant effect on the level of trade. More recently, perhaps because of the consensus view summarized above and the arrival of the euro, the focus has shifted on the economic effects of currency unions and dollarization (real and prospective). This literature is also growing very rapidly, but the consensus so far is that monetary integration has sizable trade effects. For example, Rose (2000) and Tenreyro and Barro (2003) are among the studies that conclude that a common currency enhances trade between economies.[2]

While the effects of different exchange-rate regimes on the economy are of great interest and will doubtless continue to be investigated, the present paper looks at exchange-rate variability from a different perspective. Instead of examining the consequences of exchange-rate volatility, our goal is to shed light on its causes. In particular, using an innovative technique recently employed by Stock and Watson (2002) in their study of business-cycle volatility, we will try to ascertain whether post-Bretton Woods variability in exchange rates has been the result of a less stable structure (the propagation mechanism) or more violent shocks (the impulses). Using monthly data from the US, Canada, Germany,

[1] IMF (1984) summarizes some of the early evidence.

[2] Edwards and Magendzo (2003) extend the analysis by looking at the effects of dollarization and currency unions on growth, volatility, and inflation.

and the UK, our evidence suggests that the increased volatility is entirely the result of more violent shocks, and not at all due to a less stable structure. We show that if the Bretton Woods structure had been combined with the post-Bretton Woods shocks, pre-1973 exchange rates would have been as volatile as after 1973 (and, therefore, the system would have collapsed earlier). On the contrary, if the post-Bretton Woods structure had coincided with the Bretton Woods shocks, exchange rates since 1973 would have been as stable as under Bretton Woods.

The rest of the paper is organized as follows. Section 2 discusses the econometric methodology and the sources of the data used in the estimation. Section 3 presents the empirical results and implements a number of robustness checks. Section 4 discusses the findings and some policy implications, and concludes.

2. Methodology and data sources

We begin this section with a brief description of Stock and Watson's (2002) "counterfactual VAR" method. We start by estimating reduced-form VARs for the two periods of interest. The first period is 1957:1–1971:12, under the Bretton Woods system, when exchange-rate variability was low.[3] The second period is 1973:1–2000:12, under floating exchange rates, with volatility increasing immediately and substantially. Fig. 1, the familiar plot of the logarithmic change in the monthly US nominal effective exchange rate, shows how dramatic the change is.

Suppose the VARs can be written as

$$x_t = A_i(L)x_{t-1} + u_t, \tag{1}$$

where x is the vector of the k variables included in the VAR ($k \geq 1$), i is indexing over the two time periods (i=1,2), the A's are matrices of polynomials in the lag operator L, and u is the error term with variance Σ_i in period i.

Next, define $B_i(L) = [I - A_i(L)L]^{-1}$, and let B_{ij} be the jth lag of B_i. Then, the variance of the kth series of x in the ith period is given by

$$var(x_{kt}) = \left(\sum_{j=0}^{\infty} B_{ij}\Sigma_i B'_{ij} \right)_{kk} = \sigma_k\left(A_i, \Sigma_i\right)^2. \tag{2}$$

As Stock and Watson (2002) point out, the terms in Eq. (2) can be evaluated for different A's and Σ's, making it possible to compute "counterfactual" values for the variances, i.e., values that would have been the result of different combinations of A's and Σ's than the ones actually observed.

To illustrate, assume that the (log-difference of the) exchange rate is the first variable in the VAR (k=1). We will use $\sigma_{11} = \sigma_1(A_1, \Sigma_1)$ and $\sigma_{22} = \sigma_1(A_2, \Sigma_2)$ to denote the "factual" variances of the exchange rate in periods 1 and 2, respectively. But Eq. (2) can also be used to estimate $\sigma_{12} = \sigma_1(A_1, \Sigma_2)$ as the "counterfactual" variance that would have obtained if the structure of the first period had been combined with the shocks of the second period. Similarly, $\sigma_{21} = \sigma_1(A_2, \Sigma_1)$ can be computed as another

[3] The US suspended gold sales to foreign central banks in August 1971, but it was not until December 1971 when the Smithsonian Agreement changed the official gold price from US\$35/oz to US\$38/oz. See McCallum (1996).

"counterfactual" variance, the one that would have occurred under the structure of the second period combined with the shocks of the first period. Comparing the variances will reveal how much of the increased variability is due to a change in the structure and how much is due to the shocks.

We are also interested in several of the differences between pairs of these variances and we develop a method to evaluate their statistical significance. For example, testing whether $|\sigma_{11}-\sigma_{21}|=0$, is equivalent to testing whether $\sigma_{11}=\sigma_1(A_1,\Sigma_1)$ is equal to $\sigma_{21}=\sigma_1(A_2,\Sigma_1)$; or, in other words, whether the change in the structure that occurred between the periods had a statistically significant effect on the exchange-rate variability. Similarly, testing whether $|\sigma_{11}-\sigma_{12}|=0$, amounts to testing whether $\sigma_{11}=\sigma_1(A_1,\Sigma_1)$ and $\sigma_{12}=\sigma_1(A_1,\Sigma_2)$ are equal; or, in other words, whether the change in the shocks which took place between the periods had a statistically significant effect on the volatility of the exchange rate.

Since the distribution of these statistics is unknown, both bootstrapping and Monte Carlo methods are used to obtain critical values. The original implementation of the bootstrapping algorithm to time-dependent data assumed errors that are independent and identically distributed (Effron, 1979). However, if heteroskedasticity or serial correlation exist, the randomly generated resampled data set will not preserve these properties, which will lead to inconsistent estimators. One of the proposed remedies is to use the parametric method of bootstrapping, which has been extended by Stine (1987) to an AR(p) model and by Runkle (1987) to VAR(p) model. This methodology has been applied by Inoue and Kilian (2002) to generate the confidence intervals of VAR(∞) parameters. Our work, using their methods, takes the following steps. First, an AR or VAR process of order p,

$$x_t = \beta_0 + \beta_1 x_{t-1} + \cdots + \beta_p x_{t-p} + \varepsilon_{p,t}$$

is estimated with Least Squares (LS) to obtain the LS estimate $\hat{\beta}(p)=(\hat{\beta}_0,\hat{\beta}_1,\cdots,\hat{\beta}_p)$. p is selected to remove autocorrelation and cross-correlation of the residuals. Second, including k initial observations $T+k+p$ bootstrap innovations ε_t^* where $T=p+1,\ldots,t$, are generated by random sampling with replacement from the regression residuals. Third, we generate a sequence of pseudo-data of length $T+k+p$ from the recursion $x_t^*=\hat{\beta}_0+\hat{\beta}_1^* x_{t-1}+\cdots+\hat{\beta}_p x_{t-p}^*+\varepsilon_{tt}^*$ using the vector of the initial observations $x_0^*=(x_1^*,\cdots,x_p^*)$ as starting values to preserve the scale of x_t. Fourth, factual and counterfactual variances of x_t^* were calculated after removing k initial observations. The second, third, and fourth steps are repeated for the desired number of iterations in order to build the empirical distribution of the statistics.

Following Kilian (1997), we have used $p=12$ to avoid the consequences of bootstrapping an under-parameterized model. We report the critical values based on 1000 iterations.[4] The Monte Carlo critical values are obtained using similar steps, except that the residual on the second step is replaced by $T+k+p$ independent and identically distributed random innovations μ_{t+k+p} adjusted to the same variances of the estimated residuals from the first step. An advantage of the Monte Carlo method is that the disturbance is free of serial correlation and heteroskadasticity.

All data are obtained from the IMF's International Financial Statistics. Unless otherwise indicated, all series are monthly and available from 1957:1 to 2000:12. For the US exchange rate, we use the dollar

[4] One hundred initial observations has been generated to obtain stable model.

nominal effective exchange rate (series 111..neuzf). For Canada, the UK and Germany, we use the exchange rates of the domestic currencies with respect to the US dollar.

3. Empirical evidence

3.1. A simple model

We begin by estimating the simplest model possible: a univariate version of Eq. (1) for the log-difference of the US dollar's nominal effective exchange rate. Panel A of Table 1 reports the factual and counterfactual estimated variances for the two periods for a lag length of 12. Focusing on the factual variances first, the Table makes it clear that second-period volatility (σ_{22}=3.11) is 30 times higher that first-period volatility (σ_{11}=0.10). This is impressive but not entirely surprising given the evidence of Fig. 1. Table 1 also indicates that these estimated factual variances are virtually identical to the actual sample variances, σ_1^2=0.09 and σ_2^2=3.12.

Table 1
Implied exchange-rate volatility: the US

Actual						
		σ_1^2 = 0.09		σ_2^2 = 3.12		
(A) Univariate model						
Factual			Counterfactual			
$\sigma_{11}=\sigma_1(A_1, \Sigma_1)$		$\sigma_{22}=\sigma_1(A_2, \Sigma_2)$	$\sigma_{12}=\sigma_1(A_1, \Sigma_2)$		$\sigma_{21}=\sigma_1(A_2, \Sigma_1)$	
0.10		3.11	3.93		0.08	
		$\sigma_{11}-\sigma_{21}$	$\sigma_{12}-\sigma_{22}$	$\sigma_{11}-\sigma_{12}$	$\sigma_{21}-\sigma_{22}$	$\sigma_{12}-\sigma_{21}$
		0.02	0.81**	3.83**	3.04**	3.85**
BT	95%	0.35	0.38	0.94	0.89	1.00
	99%	0.50	0.54	1.28	1.19	1.38
MC	95%	0.29	0.29	0.49	0.48	0.59
	99%	0.40	0.42	0.67	0.67	0.87
(B) Multivariate model						
Factual			Counterfactual			
$\sigma_{11}=\sigma_1(A_1, \Sigma_1)$		$\sigma_{22}=\sigma_1(A_2, \Sigma_2)$	$\sigma_{12}=\sigma_1(A_1, \Sigma_2)$		$\sigma_{21}=\sigma_1(A_2, \Sigma_1)$	
0.10		3.02	3.47		0.34	
		$\sigma_{11}-\sigma_{21}$	$\sigma_{12}-\sigma_{22}$	$\sigma_{11}-\sigma_{12}$	$\sigma_{21}-\sigma_{22}$	$\sigma_{12}-\sigma_{21}$
		0.25	0.45	3.37**	2.68**	3.13**
BT	95%	0.71	1.09	1.23	0.95	1.74
	99%	0.92	1.43	1.54	1.13	2.10
MC	95%	0.78	1.03	0.91	0.72	1.53
	99%	0.99	1.28	1.08	0.86	1.83

Period 1 is 1957:1–1971:12, and period 2 is 1973:1–2000:12. BT and MC give, respectively, Bootstrap and Monte Carlo critical values from 1000 replications.

** Denotes statistical significance at the 1% significance level.

Proceeding to the counterfactual estimates, σ_{12}, the variance that would have obtained if the first-period structure had been combined with the second-period shocks, equals 3.93, and thus is very similar in magnitude with σ_{22} and σ_2^2. In addition, σ_{21}, the counterfactual variance that would have occurred if the second-period structure had coincided with the first-period shocks, is 0.08, and so it is extremely close to the values of σ_{11} and σ_1^2. It is therefore clear that the higher volatility of the exchange rate in the post-Bretton Woods period is the result of (much) more violent shocks, rather than a less stable structure. In time-series terminology, the estimates show that the reason behind the exchange-rate volatility is the impulses and not the propagation mechanism.

Panel A of Table 1 also reports the absolute values of the differences between pairs of the variances, together with critical values that have been calculated using bootstrapping and Monte Carlo techniques. Note that $|\sigma_{11}-\sigma_{21}|$ is very small (0.02) and statistically insignificant. This suggests that changing the model's structure while keeping the same first-period shocks would make no difference for the exchange-rate variability. On the other hand, $|\sigma_{11}-\sigma_{12}|$ is both large (3.83) and decisively statistically significant. This means that changing the shocks while keeping the same first-period structure would make a big difference for volatility. Looking at the second period, $|\sigma_{12}-\sigma_{22}|$ is statistically significant, but small (0.81) relative to the actual difference in variances (3.03=3.12−0.09). Moreover, σ_{12} is greater than σ_{22}, which suggests that adopting the first-period's structure while keeping the same second-period shocks would actually *raise* exchange-rate variability. Finally, like $|\sigma_{11}-\sigma_{12}|$, $|\sigma_{21}-\sigma_{22}|$ is both large (3.04) and strongly statistically significant, implying that changing the shocks while keeping the same second-period structure would have a huge impact on volatility.

3.2. A multivariate model

In this section, we expand the estimated system to a multivariate VAR that includes a number of additional variables that are predicted by economic theory to influence exchange-rate determination. The goal is to make sure that, in using the univariate model of the previous section, we are not minimizing the importance of structural stability and/or assigning an excessively large role to the impulses because of the omission of relevant variables.

Panel B of Table 1 reports the multivariate results for the US model. In addition to the log-difference of the effective exchange rate, the estimated VARs now include the Federal Funds rate, and the log-differences of industrial production and the M2 money stock.[5] The lag length is again set at 12. The most intriguing feature of Panel B is its similarity with Panel A. Thus, σ_{11} equals 0.10 and σ_{22} is 3.02, both taking essentially the same values as in Panel A and the actual variances. Unsurprisingly, the counterfactual variances tell the same story. The estimate for σ_{12} is 3.47, and for σ_{21} is 0.34. Once more, the variance that would have obtained if the first-period structure had been combined with the second-period shocks is virtually the same with the second period's factual variance, σ_{22}. Also, the counterfactual variance that would have occurred if the second-period structure had coincided with the first-period shocks is very close to the magnitude of σ_{11}.

[5] Our general list of variables includes an output variable (industrial production or GDP, depending on the frequency of the data), the price level, a short-term interest rate, and a money aggregate. This choice is guided by theory and nests various theoretical frameworks, including purchasing power parity, interest rate parity, and the monetary approach. For recent studies that use a similar set of variables, see Bergin (2003), Faust and Rogers (2003), and Kim (2003). But see also Kilian and Taylor (2003).

The variance differences in Panel B are even more supportive of the idea that impulses, rather than propagation, are responsible for the second period's increased exchange-rate volatility. Thus, both $|\sigma_{11}-\sigma_{21}|$ and $|\sigma_{12}-\sigma_{22}|$ are small (0.25 and 0.45, respectively) and statistically insignificant. This means that changing the model's structure while keeping *either* period's shocks would make no difference for that period's exchange-rate variability. On the other hand, $|\sigma_{11}-\sigma_{12}|$ and $|\sigma_{21}-\sigma_{22}|$ are both large (3.37 and 2.68, respectively) and highly statistically significant. This implies that changing the shocks while holding constant *either* period's structure would make a big difference for volatility in that period. It follows that adding several variables to the estimated VARs does not change, and possibly strengthens, our finding that the shocks account for the entire increase in observed exchange-rate variability, while absolving the structure of any responsibility.

3.3. Three other exchange rates

As a second robustness check, we have considered three bilateral exchange rates: the US dollar rates of the Canadian dollar, the German mark, and the UK pound.[6] We begin by estimating univariate models for each of the three exchange rates, and then proceed to multivariate VARs that also include the domestic–US interest rate differential, the log-differences of the domestic and US industrial production.

Table 2 reports the estimated variances for Canada. Once again, the estimates are essentially identical for the two specifications. The first-period factual variance, σ_{11}, equals 0.36 for the univariate model and 0.35 for the multivariate, while the second-period factual variance, σ_{22}, is 1.09 in the univariate case and in the multivariate. Thus, the post-Bretton Woods variability is three times as high as that of the period before 1972. As Table 2 makes clear, these numbers are virtually identical with the actual variances for the two periods estimated as σ_1^2=0.36 and σ_2^2=1.09.

The similarities extend to the counterfactual variances. The estimate for σ_{12} is 1.11 in Panel A and 1.12 in Panel B, while σ_{21} equals 0.36 for the univariate model and 0.38 for the multivariate one. Once again, the higher volatility of the exchange rate in the post-Bretton Woods period is shown to be the result of more variable shocks, and not a less stable structure.

In terms of the variance differences, the results are qualitatively very similar to those of the multivariate US model. Thus, in both Panels A and B, both $|\sigma_{11}-\sigma_{21}|$ and $|\sigma_{12}-\sigma_{22}|$ are small (ranging from 0.005 to 0.03) and statistically insignificant, which means that changing the model's structure while holding constant either period's shocks would have no effect on that period's exchange-rate variability. Conversely, in both Panels A and B, $|\sigma_{11}-\sigma_{12}|$ and $|\sigma_{21}-\sigma_{22}|$ are large (varying from 0.71 to 0.77) and strongly statistically significant, which suggests that changing the shocks while holding constant either period's structure would have a big effect on volatility in that period. It is clear that for Canada, just like for the US, the shocks are entirely responsible for the second period's higher volatility, while the structure has played no role. Put differently, if the second-period structure had coincided with the first-period shocks, the post-1973 variance would have been no higher than σ_{11}, and this result is robust across the specifications used.

Table 3 repeats the exercise for Germany reaching essentially the same conclusions. Again, the estimated variances are very similar for the two specifications. The first-period factual variance, σ_{11}, equals 1.04 for the univariate model and 1.06 for the multivariate, while the second-period factual

[6] We also considered the US dollar exchange rate of the Japanese yen, but first-period estimation was not feasible because the rate was constant over the entire 1957–1971 period, and so σ_{11}, σ_{12}, and σ_{21} cannot be estimated.

Table 2
Implied exchange-rate volatility: Canada

Actual						
		$\sigma_1^2 = 0.36$		$\sigma_2^2 = 1.09$		
(A) Univariate model						
Factual				Counterfactual		
$\sigma_{11} = \sigma_1(A_1, \Sigma_1)$ 0.36		$\sigma_{22} = \sigma_1(A_2, \Sigma_2)$ 1.09		$\sigma_{12} = \sigma_1(A_1, \Sigma_2)$ 1.11		$\sigma_{21} = \sigma_1(A_2, \Sigma_1)$ 0.36
		$\lvert\sigma_{11}-\sigma_{21}\rvert$	$\lvert\sigma_{12}-\sigma_{22}\rvert$	$\lvert\sigma_{11}-\sigma_{12}\rvert$	$\lvert\sigma_{21}-\sigma_{22}\rvert$	$\lvert\sigma_{12}-\sigma_{21}\rvert$
		0.005	0.01	0.75**	0.74**	0.75**
BT	95%	0.13	0.13	0.31	0.30	0.36
	99%	0.18	0.20	0.40	0.39	0.45
MC	95%	0.12	0.12	0.26	0.24	0.30
	99%	0.17	0.18	0.35	0.34	0.41
(B) Multivariate model						
Factual				Counterfactual		
$\sigma_{11} = \sigma_1(A_1, \Sigma_1)$ 0.35		$\sigma_{22} = \sigma_1(A_2, \Sigma_2)$ 1.09		$\sigma_{12} = \sigma_1(A_1, \Sigma_2)$ 1.12		$\sigma_{21} = \sigma_1(A_2, \Sigma_1)$ 0.38
		$\lvert\sigma_{11}-\sigma_{21}\rvert$	$\lvert\sigma_{12}-\sigma_{22}\rvert$	$\lvert\sigma_{11}-\sigma_{12}\rvert$	$\lvert\sigma_{21}-\sigma_{22}\rvert$	$\lvert\sigma_{12}-\sigma_{21}\rvert$
		0.03	0.03	0.77**	0.71**	0.74**
BT	95%	0.25	0.32	0.39	0.33	0.54
	99%	0.30	0.41	0.45	0.39	0.62
MC	95%	0.25	0.31	0.32	0.27	0.49
	99%	0.33	0.40	0.37	0.33	0.60

Period 1 is 1957:1–1971:12, and period 2 is 1973:1–2000:12. BT and MC give, respectively, Bootstrap and Monte Carlo critical values from 1000 replications.

** Denotes statistical significance at the 1% significance level.

variance, σ_{22}, is 7.27 in the univariate case and 7.16 in the multivariate. Thus, the post-Bretton Woods variability is seven to eight times as high as that of the period before 1972. Table 3 also makes it clear that these numbers are quite close to the actual variances of σ_1^2=1.03 and σ_2^2=7.28.

The counterfactual variances paint a similar picture. The estimate for σ_{12} is 6.68 in Panel A and 7.29 in Panel B, while σ_{21} equals 1.13 for the univariate model and 1.47 for the multivariate one. Once again, the shocks seem to be solely responsible for the greater variability of the exchange rate in the post-Bretton Woods period.

Looking at the variance differences, the nature of the results is remarkably similar to those of Tables 1 and 2. Thus, in both Panels A and B of Table 3, both $|\sigma_{11}-\sigma_{21}|$ and $|\sigma_{12}-\sigma_{22}|$ are small (ranging from 0.09 to 0.59) and statistically insignificant, so that changing the model's structure while holding the shocks constant would have no effect on either period's exchange-rate variability. On the other hand, in both Panels A and B, $|\sigma_{11}-\sigma_{12}|$ and $|\sigma_{21}-\sigma_{22}|$ are large (varying from 5.64 to 6.23) and statistically significant, suggesting that changing the shocks while holding the structure constant would have a big effect on volatility in either period. The estimates of Table 3 make it apparent that, just like for the US and Canadian dollars, the reason behind the German currency's post-Bretton Woods volatility is to be found in the impulses and not the propagation mechanism.

Table 3
Implied exchange-rate volatility: Germany

Actual						
		σ_1^2 = 1.03		σ_2^2 = 7.28		
(A) Univariate model						
Factual				Counterfactual		
$\sigma_{11} = \sigma_1(A_1, \Sigma_1)$ 1.04		$\sigma_{22} = \sigma_1(A_2, \Sigma_2)$ 7.27		$\sigma_{12} = \sigma_1(A_1, \Sigma_2)$ 6.68	$\sigma_{21} = \sigma_1(A_2, \Sigma_1)$ 1.13	
		$\lvert\sigma_{11}-\sigma_{21}\rvert$	$\lvert\sigma_{12}-\sigma_{22}\rvert$	$\lvert\sigma_{11}-\sigma_{12}\rvert$	$\lvert\sigma_{21}-\sigma_{22}\rvert$	$\lvert\sigma_{12}-\sigma_{21}\rvert$
		0.09	0.59	5.64**	6.14**	5.55**
BT	95%	0.99	1.08	2.43	2.32	2.75
	99%	1.33	1.62	3.33	3.05	3.79
MC	95%	0.68	0.73	1.38	1.31	1.69
	99%	1.04	1.08	1.74	1.64	2.18
(B) Multivariate model						
Factual				Counterfactual		
$\sigma_{11} = \sigma_1(A_1, \Sigma_1)$ 1.06		$\sigma_{22} = \sigma_1(A_2, \Sigma_2)$ 7.16		$\sigma_{12} = \sigma_1(A_1, \Sigma_2)$ 7.29	$\sigma_{21} = \sigma_1(A_2, \Sigma_1)$ 1.47	
		$\lvert\sigma_{11}-\sigma_{21}\rvert$	$\lvert\sigma_{12}-\sigma_{22}\rvert$	$\lvert\sigma_{11}-\sigma_{12}\rvert$	$\lvert\sigma_{21}-\sigma_{22}\rvert$	$\lvert\sigma_{12}-\sigma_{21}\rvert$
		0.41	0.13	6.23**	5.69**	5.82**
BT	95%	2.20	3.33	3.54	2.59	5.09
	99%	2.76	4.12	4.19	3.03	6.19
MC	95%	1.77	2.43	2.49	1.95	3.87
	99%	2.31	3.27	3.10	2.41	4.85

Period 1 is 1957:1–1971:12, and period 2 is 1973:1–1998:12. BT and MC give, respectively, Bootstrap and Monte Carlo critical values from 1000 replications.

** Denotes statistical significance at the 1% significance level.

This section's last application is for the UK, reported by Table 4. Robustness is not lacking, but the results are generally less precise that for the previous three cases. The first-period factual variance, σ_{11}, equals 2.93 for the univariate model and 3.04 for the multivariate, while the second-period factual variance, σ_{22}, is 6.58 in the univariate case and 6.55 in the multivariate. Thus, the latter period's variability is twice as high as that of the period before 1972. Table 4 also shows that these estimates are very similar to the actual variances of σ_1^2=2.93 and σ_2^2=6.58.

Regarding the counterfactual variances, the estimated σ_{12} is 5.58 in Panel A but 10.79 in Panel B, while σ_{21} equals 3.46 for the univariate model and 2.02 for the multivariate one. While these estimates are more fragile than those of Tables 1–3, they continue to imply that the second period's greater exchange-rate variability is again due to the impulses rather than the propagation mechanism.

The conclusions afforded by the UK variance differences are not as sharp as those drawn for the US, Canada, and Germany, because of a general lack of precision. Qualitatively, however, the results are not surprising. Thus, in both Panels A and B of Table 4, both $|\sigma_{11}-\sigma_{12}|$ and $|\sigma_{21}-\sigma_{22}|$ tend to be larger and more statistically significant than $|\sigma_{11}-\sigma_{21}|$ and $|\sigma_{12}-\sigma_{22}|$, so that the volatility effects of changing the shocks (while keeping the structure constant) exceed the effects of changing the model's structure (while holding the shocks constant).

Table 4
Implied exchange-rate volatility: the UK

Actual						
		$\sigma_1^2 = 2.93$		$\sigma_2^2 = 6.58$		
(A) Univariate model						
Factual				Counterfactual		
$\sigma_{11} = \sigma_1\,(A_1, \Sigma_1)$ 2.93		$\sigma_{22} = \sigma_1\,(A_2, \Sigma_2)$ 6.58		$\sigma_{12} = \sigma_1\,(A_1, \Sigma_2)$ 5.58	$\sigma_{21} = \sigma_1\,(A_2, \Sigma_1)$ 3.46	
		$\lvert\sigma_{11} - \sigma_{21}\rvert$	$\lvert\sigma_{12} - \sigma_{22}\rvert$	$\lvert\sigma_{11} - \sigma_{12}\rvert$	$\lvert\sigma_{21} - \sigma_{22}\rvert$	$\lvert\sigma_{12} - \sigma_{21}\rvert$
		0.53	1.01	2.65^{+}	3.13^{++}	2.12
BT	95%	1.57	1.86	4.50	4.10	4.80
	99%	2.39	2.86	5.77	5.25	6.42
MC	95%	1.39	1.72	2.41	2.05	3.31
	99%	1.75	2.28	3.19	2.70	4.34
(B) Multivariate model						
Factual				Counterfactual		
$\sigma_{11} = \sigma_1\,(A_1, \Sigma_1)$ 3.04		$\sigma_{22} = \sigma_1\,(A_2, \Sigma_2)$ 6.55		$\sigma_{12} = \sigma_1\,(A_1, \Sigma_2)$ 10.79	$\sigma_{21} = \sigma_1\,(A_2, \Sigma_1)$ 2.02	
		$\lvert\sigma_{11} - \sigma_{21}\rvert$	$\lvert\sigma_{12} - \sigma_{22}\rvert$	$\lvert\sigma_{11} - \sigma_{12}\rvert$	$\lvert\sigma_{21} - \sigma_{22}\rvert$	$\lvert\sigma_{12} - \sigma_{21}\rvert$
		1.03	4.23	7.75	4.54	8.77
BT	95%	5.28	12.19	11.07	4.93	15.26
	99%	8.89	21.40	16.17	5.90	24.06
MC	95%	4.53	10.79	10.14	4.55	14.22
	99%	5.82	13.52	12.47	4.98	17.39

Period 1 is 1964:1–1971:12, and period 2 is 1973:1–2000:12. BT and MC give, respectively, Bootstrap and Monte Carlo critical values from 1000 replications.
+ and ++ Denote statistical significance at the1% and 5% levels for only MC critical values respectively.

3.4. Other robustness checks

We have performed a number of other robustness checks in order to make sure that our conclusions are not dependent on the specifications outlined above.

First, we experimented with various lag lengths, in both the univariate and multivariate specifications. Second, we tried a number of different sets of variables in the VARs. Third, we considered the relationship between the Stock–Watson approach followed here and the standard GARCH methodology, which also provides a model for volatility. Fourth, we estimated the univariate and several multivariate models with quarterly data, replacing industrial production by real GDP in the multivariate specifications.

While most of these results are not reported because of space considerations,[7] the results were found to be consistent with our central conclusion in all cases. For example, we included a number of additional variables, such as oil prices and trade balance data in the VAR, to ensure that omitting potentially important variables does not create a bias in favor of impulses rather than structure.[8] When the change in

[7] All results are available on request.
[8] We are grateful to an anonymous referee for emphasizing this.

the price of oil is included in the models, the relative importance of the shocks is not just maintained, but actually exaggerated: σ_{12} is not just higher than σ_{11}, but also substantially, and statistically significantly, higher than σ_{22} in most cases.[9] We think this exaggerated result is implausible and we attribute it to the fact that the oil price is essentially flat during the Bretton Woods period, so that the role of the shocks in the post-Bretton Woods period, when oil shocks become prominent, is artificially magnified. We also included variables based on the trade balance (with quarterly data—see below), to capture its possible exchange-rate effects. We tried the growth rate of the trade balance and the trade balance as a fraction of GDP, but our conclusions were essentially unchanged.

We gave serious thought to the relationship between the Stock–Watson counterfactual technique and the more familiar GARCH methodology.[10] A suitably modified GARCH approach would allow us to focus on the conditional variance of the second moment, conditional on the assumed structure of the first moment, thereby providing valuable answers, but to a somewhat different set of questions from the ones we ask here. Towards this end and using the lag operator notation where x is our subject series, we estimated a "vanilla" GARCH(1,1) model of the form.

$$\phi(L)_i x_t = e_t$$
$$\delta(L)_i \hat{e}_t^2 = \gamma(L)_i u_t \tag{3}$$

where $\phi(L)_i$ is the first moment autoregressive term estimated for period i, which we assumed to contain six lags, $\delta(L)_i$ is the second moment autoregressive term estimated for period i, and $\gamma(L)_i$ is the second moment moving average term estimated for period i. The first moment residual is e_t while in the second moment equation we are estimating $\hat{e}_t^2$ which has an error term u_t. Define κ_{i_mn} as the variance of the conditional second moment for period i using the structure of period m ($\phi(L)_m$) and the second moment parameters of period n ($\delta(L)_n$ and $\gamma(L)_n$). Looking only at the US data, we find that κ_{1_11}=0.07775 and κ_{2_22}=2.74499.[11] The magnitudes of these unconstrained models should be compared to estimating the first period GARCH model conditional on the second moment parameters from the second period κ_{1_12}=0.08829 and estimating the first period GARCH model conditional on constraining the first moment structure from the second period κ_{1_21}=0.07664. Since $\kappa_{1\_21}<\kappa_{1\_12}$ and κ_{1_21} is closer to κ_{1_11}, it suggests that it was the changes in the parameters of the second moment in the second period that made the difference. Looking at the second period, we find a similar story. Here, κ_{2_12}=3.50516 and κ_{2_21}=4.15304. Since κ_{2_12} is closer to the unconstrained model κ_{2_22} than κ_{2_21}, again, it is the changes in the second moment coefficients that is making the most difference. In summary, while the GARCH models are necessarily focused on the conditional second moment variance, rather than the first moment, and in addition are not true counterfactuals such as in the Stock–Watson approach due to having to be estimated in constrained form, nevertheless, the results with this approach are consistent with what was found with the Stock–Watson approach.

As another robustness example, Table 5 reports the univariate quarterly estimates for all four exchange rates, where the two time periods for each country are defined as in Tables 1–4. The thing to emphasize is that the estimated variances reported in Table 5 follow a pattern that is familiar from the first four tables. In particular, and in every single case, σ_{21} is much closer to σ_{11} than to σ_{22}. This implies

[9] In the multivariate US model with oil prices, for example, σ_{11}=0.09, σ_{22}=3.00, but σ_{12}=4.93.

[10] We thank an anonymous referee for bringing this to our attention.

[11] Estimation was done with the RATS 5.03 software system.

Table 5
Implied exchange-rate volatility: quarterly univariate models

		US	Canada	UK	Germany
Factual	$\sigma_{11}=\sigma_1(A_1,\Sigma_1)$	0.81	1.00	2.61	1.38
	$\sigma_{22}=\sigma_1(A_2,\Sigma_2)$	10.32	2.85	24.26	24.71
Counterfactual	$\sigma_{12}=\sigma_1(A_1,\Sigma_2)$	31.65	2.52	28.59	29.95
	$\sigma_{21}=\sigma_1(A_2,\Sigma_1)$	0.26	1.13	2.22	1.13
	$\lvert\sigma_{11}-\sigma_{21}\rvert$	0.55	0.13	0.39	0.24
	$\lvert\sigma_{12}-\sigma_{22}\rvert$	21.33**	0.33	4.33*	5.24*
	$\lvert\sigma_{11}-\sigma_{12}\rvert$	30.84**	1.53*	25.98**	28.58**
	$\lvert\sigma_{21}-\sigma_{22}\rvert$	10.05**	1.73**	22.04**	23.58**
	$\lvert\sigma_{12}-\sigma_{21}\rvert$	31.38**	1.40++	26.37**	28.82**

* Denotes statistical significance at the 5% level for both tests.

** Denotes statistical significance at the 1% level for both tests.

++ Denotes statistical significance at the 1% level for MC critical values only.

that a (counterfactual) combination of the Bretton Woods shocks with the post-Bretton Woods structure would have produced a variance closer to first period's. On the contrary, σ_{12} is always considerably closer to σ_{22} than to σ_{11}. This means that a (hypothetical) combination of the Bretton Woods structure with the post-Bretton Woods shocks would have resulted in a variance closer to second period's.

4. Discussion and conclusions

Why has exchange-rate volatility increased so much since the collapse of the Bretton Woods system? One possible answer is that the economic structure determining the value of exchange rates underwent a significant change, most likely as a direct result of the change in regime, making it sufficiently less stable to account for the entire increase in volatility. Another possibility is that the structure remained essentially the same, and the increased variability is entirely the result of a more volatile economic environment, characterized by more violent economic shocks. A third, and a priori more plausible answer, is one that combines the first two, assigning some of the blame to the structure (the propagation mechanism) and the rest to the shocks (the impulses).

This paper has investigated the issue using an econometric technique employed by Stock and Watson (2002) in their study of business-cycle volatility. Using monthly and quarterly data from the US, Canada, Germany, and the UK, we have estimated several exchange-rate models over two time periods: 1957–1971, a Bretton Woods period, and 1973–2000, the post-Bretton Woods period. The estimates have allowed us to calculate "counterfactual" variances for the exchange rates; i.e., the hypothetical variances that would have obtained if one period's structure had been combined with the other period's shocks. Comparing these values to the actual variances observed (or estimated) for the two periods, it becomes possible to compare the relative contribution of propagation and impulses to the higher variability.

Our results are very easy to summarize. We find that the increased exchange-rate volatility is entirely the result of more violent shocks and not at all due to a less stable structure. Put differently, we show that if the Bretton Woods structure had been combined with the post-Bretton Woods shocks, pre-1973 exchange rates would have been as volatile as they turned out to be after 1973. Conversely, if the post-

Bretton Woods structure had been combined with the Bretton Woods shocks, exchange rates since 1973 would have been as stable as they were under Bretton Woods. These results hold for all different exchange rates, all estimated models, and both data frequencies examined.

What is the economic significance of these results? Consider first the finding that the Bretton Woods volatility would have been as high as that of the post-1973 period, if the Bretton Woods structure had coincided with the more recent period's shocks. This implies that, in that hypothetical case, the system would have been under much more strain and, likely, would have collapsed at a much earlier date. Next, consider the finding that the post-Bretton Woods exchange rates would have been as tranquil as under Bretton Woods, if the post-1973 structure had coincided with the earlier period's shocks. This suggests that the change in exchange-rate regime *by itself* is not at all responsible for the higher observed volatility. In fact, combining the two arguments of this paragraph, it can be argued that the change in the exchange-rate regime that occurred in the early 1970s is more accurately portrayed as the consequence, rather than the cause, of a dramatically higher volatility.[12]

A question, of course, that remains is what have been the causes of the more volatile shocks in the post-Bretton Woods period, and whether one of these causes may have been indirectly linked to the regime change itself. Although beyond the scope of the present paper (and probably not amenable to the methodology employed here), this is a very interesting question for future research.

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[12] As Monacelli (2004, p. 192) observes, "it could also be argued that the choice of the exchange rate regime is endogenous, and that it is indeed those countries experiencing large real shocks that choose to switch to floating exchange rates". Monacelli (2004) does not think this is plausible, but he points out that it would be consistent with a Mundell–Fleming normative view.

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