Risk Matters: A Comment

By Benjamin Born and Johannes Pfeifer*

We show that the risk-shock business cycle model of Jesús Fernández-Villaverde, Pablo A. Guerrón-Quintana, Juan F. Rubio-Ramírez and Martín Uribe (2011) must be recalibrated because it underpredicts the targeted business cycle moments by a factor of three once a time aggregation error is corrected. Recalibrating the corrected model for the benchmark case of Argentina, the peak response and the contribution of interest rate risk shocks to business cycle volatility increase. However, the recalibrated model does worse in capturing the business cycle properties of net exports once an additional error in the computation of net exports is corrected.

JEL: E32, E43, F32, F44

Keywords: Interest Rate Risk, Stochastic Volatility

Fernández-Villaverde et al. (2011) (FGRU subsequently) find that risk shocks – mean preserving spreads to shock distributions – are an important factor in explaining business cycles in emerging market economies. Their results and methods have already spurred further work on the role of risk shocks for macroeconomic fluctuation (e.g. Martin M. Andreasen (2012), Yusuf Soner Başkaya, Timur Hülagü and Hande Küşük (2013), Susanto Basu and Brent Bundick (2012), Benjamin Born and Johannes Pfeifer (2014), Jesús Fernández-Villaverde, Pablo A. Guerrón-Quintana, Keith Kuester and Juan F. Rubio-Ramírez (2012), and Michael Plante and Nora Traum (2012)). To establish the importance of risk shocks in emerging market economies, FGRU use data for Argentina, Brazil, Ecuador, and Venezuela to calibrate a model of a small open economy subject to shocks to the level and volatility of interest rates. FGRU then report two sets of results for their calibrated model. The first set of

* Born: University of Mannheim, L7, 3-5, 68131 Mannheim, Germany, and CESifo (Germany) (e-mail: born@uni-mannheim.de); Pfeifer: University of Mannheim, L7, 3-5, 68131 Mannheim, Germany (e-mail: pfeifer@uni-mannheim.de). Special thanks go to Antonio Ciccone and Juan Rubio-Ramírez. We are also grateful to two anonymous referees, Klaus Adam, Michael Evers, and Gernot Müller for very helpful suggestions and discussions. All remaining errors are of course our own. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

results is used to gauge the success of the calibration by comparing six predicted moments – four of them targeted and two of them untargeted – with the corresponding moments in the data (the untargeted moments being the volatility and cyclicality of net exports). The second set shows the predicted response of main macroeconomic variables, like output and consumption, to risk shocks.

We argue that these results are affected by two coding issues. The first coding issue is in the time aggregation of flow variables from months to quarters. The correct time aggregation mechanically reduces the volatility of the main flow variables and the effect of risk shocks on these variables by a factor of three for any given calibration. However, as the volatilities of the main flow variables are targeted moments in the calibration, it is a priori unclear how the correct time aggregation changes the impact of risk shocks on aggregate variables once the model is recalibrated. When we recalibrate the corrected model for the benchmark case of Argentina, we actually find that risk shocks matter more for output: the peak effect of a risk shock on output turns out to be 63 percent higher than reported by FGRU and the contribution of interest rate risk shocks to business cycle volatility more than doubles (to 9 percent).

A second coding issue is in the computation of net exports and affects the cyclicality and volatility of net exports (the two untargeted moments discussed in FGRU). When we correct the computation, we find that net exports are predicted to be procyclical instead of approximately acyclical as reported in FGRU. This continues to be the case in the recalibrated and corrected model. Hence, the model fails to capture the empirically countercyclical behavior of net exports documented in FGRU and the emerging market business cycle literature (see e.g. Mark Aguiar and Gita Gopinath, 2007; David K. Backus, Patrick J. Kehoe and Finn E. Kydland, 1992; Javier García-Cicco, Roberto Pancrazi and Martín Uribe, 2010; Pablo A. Neumeyer and Fabrizio Perri, 2005). Furthermore, the recalibrated corrected model predicts that net exports are 2 to 3 times more volatile than in the data. The failure of FGRU's model to generate the cyclicality and volatility of net exports in the data may indicate that it does not appropriately capture how small open economies interact with the rest of the world at business cycle frequencies. Given the central role of the trade balance in business cycles in emerging economies (García-Cicco, Pancrazi and Uribe, 2010), this suggests that further research on the contribution of risk shocks to emerging market business cycles is needed.

The rest of the paper proceeds as follows. Section I deals with the time aggregation and Section II with the computation of net exports. Section III concludes.[1]

I. Time Aggregation

FGRU set up their model in monthly terms, but report results at quarterly frequency as most data are available at quarterly frequency only. They aggregate monthly output, consumption, investment, and hours worked to quarterly frequency by summing up monthly percentage deviations.[2] However, for flow variables expressed in percentage deviation terms, the correct way to aggregate is to average the monthly values. For example, if monthly GDP is 100 in steady state, a one percent GDP deviation from steady state for one month corresponds to a deviation of one third of a percent (1/300) for quarterly GDP. The correct time aggregation mechanically reduces the predicted volatility of the main flow variables and the predicted effect of risk shocks on these variables by a factor of three for any given set of model parameters. This is illustrated in Table 1, which shows the predicted moments reported in FGRU, the predicted moments when time aggregation is corrected but model parameters are kept at the values calibrated by FGRU, and the moments in the data.[3] It can be seen that correct time aggregation implies that FGRU's calibrated model underpredicts the data moments by a factor of three. As FGRU's calibration method targets the moments for output, consumption, and investment, this implies that the model needs to be recalibrated.

The model is calibrated to monthly frequency and most parameters are fixed to either standard values in the literature or to match great ratios. Four remaining parameters, i) the standard deviation of TFP shocks σ_x, ii) the Lawrence J. Christiano, Martin Eichenbaum

[1] Minor points and technical descriptions of the algorithms used are relegated to the online appendix. We use FGRU's first stage estimates for the exogenous processes and the same notation, focusing on their benchmark case of Argentina with uncorrelated shocks (termed M1 in FGRU).

[2] Specifically, for the moment computations, the percentage deviations are from the deterministic steady state and for the impulse response functions (IRFs) from the ergodic mean in the absence of shocks (EMAS) (see Appendix I.B for details). We use the term EMAS for FGRU's concept of "[s]tarting from the ergodic mean and in the absence of shocks" (p. 10 in their technical appendix).

[3] The effect of correct time aggregation keeping all model parameters at the values calibrated by FGRU on the IRFs is detailed in Appendix IV.

Table 1—Targeted Moments

	σ_Y	σ_C/σ_Y	σ_I/σ_Y	$\widetilde{NX}/\widetilde{Y}$
FGRU	5.30	1.54	3.90	1.75
Corr. Aggreg.	1.77	1.53	3.90	1.75
Recalibration	4.77	1.31	3.81	1.78
Data	4.77	1.31	3.81	1.78

Note: First row: moments reported in FGRU. Second row: FGRU with corrected time aggregation. Third row: moments obtained from simulating the recalibrated corrected model 200 times for 96 periods using the same pruning, simulation, filtering, and winsorizing scheme as FGRU. Fourth row: Moments obtained from HP-filtered data (1993Q1 - 2004Q3).

and Charles L. Evans (2005)-type investment adjustment costs parameter ϕ, iii) the steady state debt level $\bar{D}$, measured in output units, and iv) the holding costs of debt Φ_D, are chosen by a moment matching procedure that minimizes a quadratic form of the distance of the model moments to the data moments. The targets are four moments in quarterly data: i) output volatility, ii) the volatility of consumption relative to output, iii) the relative volatility of investment to output, and iv) the ratio of net exports over output. The net exports share in output differs from the other three moments as it is not targeted at the ergodic mean, but at the ergodic mean in the absence of shocks, $\widetilde{NX}/\widetilde{Y}$.[4] Our calibration follows the moment matching approach in FGRU and also uses their pruning and simulation scheme together with the same winsorized shocks. See Appendix V for details.

Table 2—Parameters Obtained by Moment Matching

	Φ_D	$\bar{D}$	ϕ	σ_x
Recalibration	5.92e-04	18.80	47.84	0.040
FGRU	1.00e-03	4.00	95.00	0.015

Note: first row: parameters obtained by moment matching using the corrected model. Second row: parameters obtained by moment matching in FGRU.

The third row of Table 1 shows that the moment matching is successful: choosing the four parameters allows to exactly match the four moments. From the parameter estimates

[4]There is also a minor coding issue in the computation of the net exports to output share at the EMAS in FGRU that we correct. See Appendix I.D for details.

reported in Table 2 it can be seen that moment matching using the corrected model implies a volatility of TFP shocks that is 2.7 times the volatility in FGRU.[5] As documented in FGRU, TFP shocks alone do not result in a sufficient response of investment and consumption to match their volatility relative to output. Given that the amount of interest volatility is fixed by FGRU's first stage estimates of the exogenous processes, the transmission mechanism has to adjust. This is achieved by a halving of the investment adjustment and portfolio holding costs, which brings the investment adjustment costs to a more conventional level. The portfolio holding cost parameter is now estimated to be even closer to the value of $\Phi_D = 4.2e\text{-}4$ found in Martín Uribe and Vivian Z. Yue (2006) for a panel of emerging economies. The steady state debt level more than quadruples relative to FGRU, but, given the strong non-linearities in the model, this only results in around twice the debt level in the ergodic mean.[6]

Figure 1 depicts the IRFs for the recalibrated model together with the original IRFs reported in FGRU. As can be seen, a one standard deviation risk shock now leads to a 63 percent larger output drop than originally reported in FGRU. This is mostly driven by a bigger response of consumption and investment due to stronger deleveraging. The optimal deleveraging is stronger compared to the original FGRU calibration, because both the estimated debt level is higher, making debt more risky, and the estimated investment adjustment and portfolio holding costs are lower, making it less costly to decrease debt.

To judge the importance of risk shocks for business cycle moments, it is instructive to consider a variance decomposition. Due to the non-linearity of the model and the resulting interaction of shocks, such a variance decomposition cannot be performed analytically. One way to gauge the relative importance of shocks is simulating the model with only a subset of the shocks. We follow FGRU and consider six cases: i) with all shocks, ii) using only TFP shocks while shutting off both level and volatility shocks to the interest rate in the form of the T-bill rate and the risk spread, iii) using only TFP and level shocks to the interest

[5]In the corrected FGRU model, the output volatility was 1.77 percent compared to 4.77 percent in the data. Given the fixed first stage estimates for the interest rate processes, the required 2.69 fold increase in output volatility is achieved by increasing TFP volatility by almost exactly this amount. In quarterly terms, our new estimates correspond to a TFP shock volatility of 5.5 percent and a TFP volatility of 12.3 percent.

[6]In the ergodic mean, this corresponds to an annual debt to GDP ratio of 12 percent compared to 6 percent in FGRU (see Appendix VII). According to Carmen M. Reinhart and Kenneth Rogoff (2009), the actual value of Argentinean external debt was 65 percent during the sample considered here.

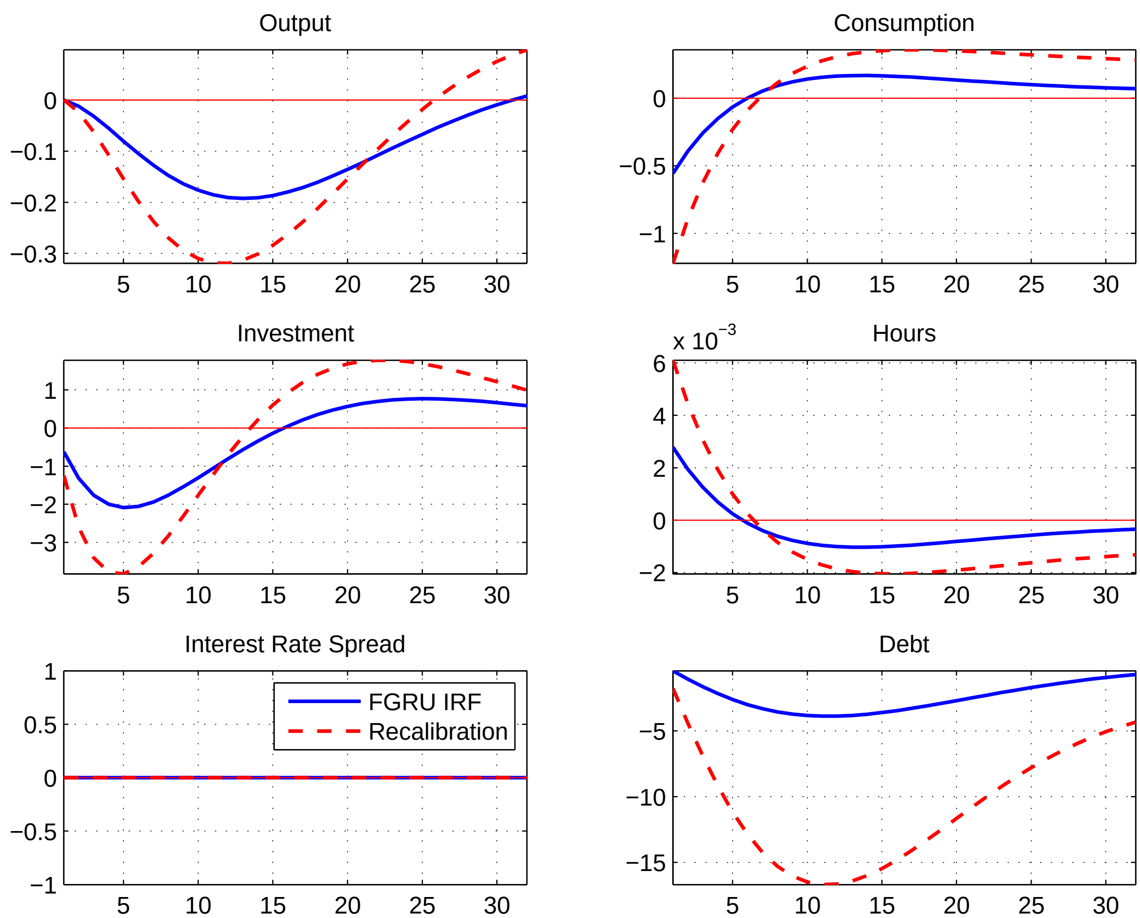

Figure 1. Comparison of original IRFs vs. IRFs of the recalibrated model

Note: blue solid line: IRFs at the EMAS reported in FGRU; red dashed line: IRFs at quarterly frequency for the recalibrated corrected model

rate, iv) using only the level shocks to the interest rate, v) level and volatility shocks to the interest rate and no TFP shocks, vi) only volatility shocks. Table 3 shows the results for the recalibrated model. Compared to FGRU, the contribution of volatility shocks to the standard deviation of output, consumption, and investment increases by factors of 2.6, 2.4, and 2, respectively. Volatility shocks alone account for 9 percent of output volatility and one third of investment volatility in the recalibrated corrected model.

II. The Cyclicality and Volatility of Net Exports

FGRU compute the quarterly absolute deviation of net exports from the deterministic steady state in their model solution using the national income accounting identity based on

Table 3—Variance Decomposition

	Data	i) All Shocks	ii) TFP Only	iii) w/o Vola	iv) Rate Level	v) w/o TFP	vi) Vola Only
σ_y	4.77	4.77	4.47	4.52	0.60	1.17	0.42
σ_c	6.25	6.25	3.01	4.20	3.08	5.44	1.87
σ_i	18.17	18.17	6.37	11.37	9.31	16.81	6.14

Note: first column: moments obtained from HP-filtered data (1993Q1 - 2004Q3); second column: 200 simulations of the recalibrated model; third column: TFP shocks only; fourth column: without volatility shocks to spread and T-Bill rate; fifth column: only level shocks to the spread and the T-Bill rate; sixth column: without TFP shocks; seventh column: only shocks to the volatility of spreads and the T-Bill rate.

quarterly output, consumption, and investment, using the formula

$$NX_t - \overline{NX} = \hat{Y}_t - \hat{C}_t - \hat{I}_t \,. \tag{1}$$

Here, hats denote percentage deviations from the deterministic steady state and bars denote steady state values, that is e.g. $\hat{Y}_t = (Y_t - \bar{Y})/\bar{Y}$. However, the correct formula weights the percentage deviations of output, consumption, and investment by their respective steady state values:

$$NX_t - \overline{NX} = \bar{Y}\hat{Y}_t - \bar{C}\hat{C}_t - \bar{I}\hat{I}_t \,. \tag{2}$$

The second and third columns of Table 4 report the volatility and cyclicality of net exports when the time aggregation error and the error in the computation of net exports are corrected but the structural parameters are kept at the values calibrated in FGRU. There are two main differences between the results reported by FGRU and the results in the corrected model.[7] First, net exports turn from approximately acyclical in FGRU to procyclical in the corrected model. The reason why net exports become procyclical when the computation of net exports is corrected is that equation (2) puts a relatively larger weight on output fluctuations than equation (1) due to output in steady state being greater than both consumption and investment.[8] This increase in the weight of the "output component" of net exports

[7]The weighting issue also affects the current account implications after risk shocks reported in Figure 6 of FGRU. An updated version of the figure can be found in Appendix III.

[8]In equation (1) all three components entered with an equal weight of 1, while equation (2) implies

mechanically increases the comovement of net exports with output and hence increases the procyclicality. The procyclicality of net exports in the corrected model contrasts with mostly countercyclical net exports in the data. Explaining this behavior has motivated prominent papers arguing for the importance of permanent TFP shocks (e.g. Aguiar and Gopinath, 2007) and financial frictions (e.g. García-Cicco, Pancrazi and Uribe, 2010).

Table 4—Cyclicality and Volatility of Net Exports

	Orig. Calib.			Recalib.	Data
	FGRU	TA	TA+NX	TA+NX	
$\rho_{NX,Y}$	0.05	0.05	0.43	0.43	-0.76
σ_{NX}/σ_Y	0.48	1.43	1.63	1.08	0.39
$\rho_{NX/Y,Y}$	-	-	-	0.41	-0.75
$\sigma_{NX/Y}$	-	-	-	6.55	3.47

Note: first column: moments reported in FGRU. Second column: moments correcting the time aggregation (TA). Third column: moments correcting the time aggregation and net export computation (TA+NX). Fourth column: moments obtained from the recalibrated corrected model. Fifth column: moments obtained from HP-filtered data. Simulations are conducted with 200 repetitions of 96 periods using the same pruning, simulation, filtering, and winsorizing scheme as FGRU. Upper panel: based on CNR-approximation to net exports. Bottom panel: based on net-export-to-output ratio.

The second main difference between the results reported by FGRU and the results in the corrected model is that the corrected model predicts a different relative volatility of net exports than the 0.48 reported in FGRU (see Table 4 and Appendix II). Correcting time aggregation, the relative net export volatility increases by a factor of three to 1.43, because the time aggregation error only affects output volatility (FGRU obtain the volatility of net exports directly at quarterly frequency). Correcting the computation of net exports leads to a minor further change in relative volatility. As a result, the corrected relative volatility is approximately 3.4 times the value reported in FGRU. The fourth column of Table 4 reports the volatility and cyclicality of net exports in the recalibrated corrected model. The model continues to predict a positive correlation (0.43) of net exports with output. Regarding volatility we find that the recalibrated corrected model overpredicts the relative volatility of net exports to the volatility of output by a factor of 2.8.

Another complication derives from the poor numerical convergence behavior of FGRU's

relative weights of 1, 0.84, and 0.13, for output, consumption, and investment, respectively.

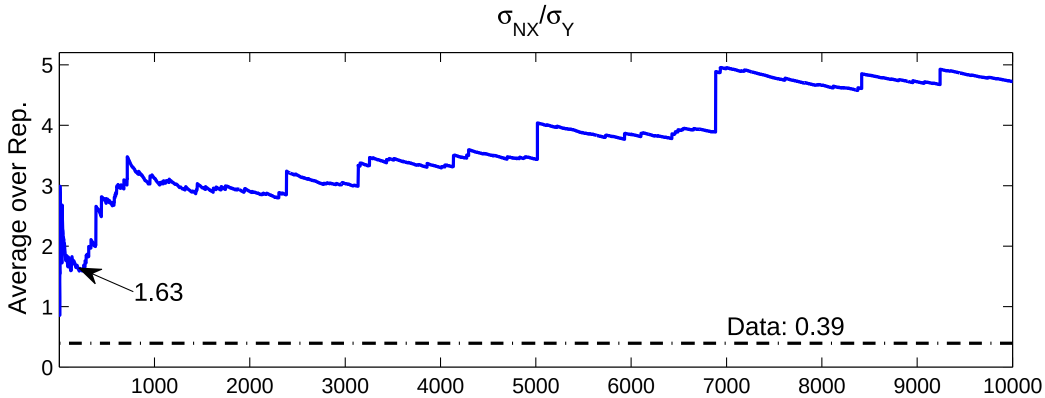

FIGURE 2. CONVERGENCE BEHAVIOR OF THE RELATIVE NET EXPORT VOLATILITY STATISTIC

Note: relative volatility of net exports to output σ_{NX}/σ_Y. Net exports transformed to percentage deviations using the CNR-approximation. The blue solid line shows the mean standard deviation (y-axis) over the up to 10,000 samples (x-axis) of simulating 96 months of data. The black dashed dotted line shows the actual data moments. The data are based on the corrected aggregation and net export computation. The black arrow indicates the value after 200 replications.

measure of net export volatility. Because net exports can be negative, instead of using a log-linear approximation, FGRU use the Isabel Correia, Joao C. Neves and Sergio Rebelo (1995)(CNR subsequently)-approximation of the net exports

$$\widehat{NX}_t \equiv \frac{NX_t}{|\,\mathrm{mean}(NX_t)|} - 1\,. \tag{3}$$

This formula takes the percentage deviations from the absolute value of the mean in order to preserve the sign. If the mean of net exports is close to 0, this can have drawbacks in short simulations where the mean is imprecisely estimated.

This issue is illustrated in Figure 2. On the vertical axis the figure displays the volatility of net exports relative to the volatility of output (blue solid line), computed with the CNR-approximation as in FGRU but correcting the time aggregation error affecting output volatility and the error in the computation of net exports. The horizontal axis displays the number of simulation repetitions over which the relative volatility has been computed. As in FGRU, each repetition is based on a simulation of 96 time periods. The black arrow marks 200 simulations, which is the number of simulation repetitions that FGRU use to obtain the predicted relative volatility of net exports reported in Table 4. The figure suggests the simulated value of σ_{NX}/σ_Y varies substantially with the number of repetitions, even when we go to more than the 200 repetitions used by FGRU.[9]

In the bottom panel of Table 4 we therefore also examine the volatility of the net exports to output ratio, NX_t/Y_t. Due to this ratio being scaled with output, it does not suffer from the same division by (almost) zero problem (see Appendix VI). It can be seen that with this measure of the volatility of net exports, the model prediction is closer to the data than with the CNR-measure used by FGRU. But the predicted volatility is still almost twice the volatility of the net exports to output ratio in the data.

III. Conclusion

FGRU find that risk shocks have important effects on aggregate variables and might contribute to explaining the current account movements of small open developing economies. We noted an error in the time aggregation of flow variables that results in the calibrated model not matching the targeted data moments. Correcting this error and recalibrating the model to fit the volatilities of output, consumption, and investment, we find that the peak effect of a risk shock on output and the business cycle contribution of volatility shocks both increase.

We also pointed to a weighting error in the net export computation that affects the cyclicality and volatility of net exports – the two untargeted moments discussed in FGRU. In the corrected and recalibrated model, net exports turn out to be procyclical. This is at odds with countercyclical net exports in emerging markets, one of the most robust stylized facts documented in the emerging markets business cycles literature. Moreover, the corrected and recalibrated model overpredicts the volatility of net exports by a factor of 2 to 3. The failure of FGRU's model to capture the cyclicality and volatility of net exports suggests that further research on the contribution of risk shocks to emerging market business cycles is needed.

REFERENCES

Aguiar, Mark, and Gita Gopinath. 2007. "Emerging market business cycles: the cycle is the trend." *Journal of Political Economy*, 115: 69–102.

[9]The convergence problem is driven by the numerator σ_{NX}, while the denominator σ_Y converges quickly. Moreover, the convergence problem only affects the volatility of net exports, but not its correlation with output.

Andreasen, Martin M. 2012. “An estimated DSGE model: explaining variation in nominal term premia, real term premia, and inflation risk premia.” *European Economic Review*, 56: 1656–1674.

Backus, David K., Patrick J. Kehoe, and Finn E. Kydland. 1992. “International real business cycles.” *Journal of Political Economy*, 100(4): 745–75.

Başkaya, Yusuf Soner, Timur Hülagü, and Hande Küşük. 2013. “Oil price uncertainty in a small open economy.” *IMF Economic Review*, 61(1): 168–198.

Basu, Susanto, and Brent Bundick. 2012. “Uncertainty shocks in a model of effective demand.” NBER Working Papers 18420.

Born, Benjamin, and Johannes Pfeifer. 2014. “Policy risk and the business cycle.” *Journal of Monetary Economics*, 68: 68–85.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. 2005. “Nominal rigidities and the dynamic effects of a shock to monetary policy.” *Journal of Political Economy*, 113(1): 1–45.

Correia, Isabel, Joao C. Neves, and Sergio Rebelo. 1995. “Business cycles in a small open economy.” *European Economic Review*, 39(6): 1089–1113.

Fernández-Villaverde, Jesús, Pablo A. Guerrón-Quintana, Juan F. Rubio-Ramírez, and Martín Uribe. 2011. “Risk matters: the real effects of volatility shocks.” *American Economic Review*, 101(6): 2530–61.

Fernández-Villaverde, Jesús, Pablo A. Guerrón-Quintana, Keith Kuester, and Juan F. Rubio-Ramírez. 2012. “Fiscal volatility shocks and economic activity.” University of Pennsylvania Mimeo.

García-Cicco, Javier, Roberto Pancrazi, and Martín Uribe. 2010. “Real business cycles in emerging countries?” *American Economic Review*, 100(5): 2510–31.

Neumeyer, Pablo A., and Fabrizio Perri. 2005. “Business cycles in emerging economies: the role of interest rates.” *Journal of Monetary Economics*, 52(2): 345–380.

Plante, Michael, and Nora Traum. 2012. "Time-varying oil price volatility and macroeconomic aggregates." Caepr Working Papers 2012-002.

Reinhart, Carmen M., and Kenneth Rogoff. 2009. *This time is different: eight centuries of financial folly.* Princeton University Press.

Uribe, Martín, and Vivian Z. Yue. 2006. "Country spreads and emerging countries: who drives whom?" *Journal of International Economics*, 69(1): 6–36.