Essays on Macroeconomics

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ABSTRACT

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This dissertation is a collection of three essays on macroeconomics, examining the sources of business cycles. In particular, we are interested in understanding how shocks propagate over the business cycle in both closed economy and open economy settings. The common approach we take in these chapters is to use both theory and data in a structural estimation based on a dynamic stochastic general equilibrium model.

In the first chapter, motivated by the correlation of business cycles across countries, we provide a new empirical evidence about the role of common shocks in business cycles for small open economies. Specifically, we conduct a structural estimation of a small open economy real business cycle model featuring a realistic debt adjustment cost and common shocks. Using a novel dataset for 17 small developed and developing countries between 1900 and 2006, we find that common shocks are a primary source of business cycles, explaining nearly 50% of the output fluctuations over the last 100 years in small open economies. The estimated common shocks capture important historical episodes such as the Great depression, the two World Wars and the two oil price shocks. Moreover, these common shocks are important for not only small developed countries but also developing countries. We point out the importance of our structural approach in identifying the sizable role of both productivity and other common shocks such as interest rate premium shocks. The reduced form dynamic factor model approach in the previous literature, which often assumes one type of common component, would predict only a third of the contribution estimated in the structural model.

In the second chapter, we focus on the transmission from one country to another through international trade. First, we argue that while we observe substantial business cycle corre-

lation across countries, especially among developed economies, most existing models are not able to generate strong transmission of shocks endogenously through international trade. In the framework of structural model, we show that the nature of such transmission depends fundamentally on the features determining the responsiveness of labor supply and labor demand to international relative prices. We augment a standard international macroeconomic model to incorporate three key features: a weak short run wealth effect on labor supply, variable capital utilization, and imported intermediate inputs for production. This model can generate large and significant endogenous transmission of technology shocks through international trade. We demonstrate this by estimating the model using data for Canada and the United States with quasi-Bayesian methods. We find that this model can account for the substantial transmission of permanent U.S. technology shocks to Canadian aggregate variables such as output and hours documented in a structural vector autoregression. Transmission through international trade is found to explain the majority of the business cycle comovement between the United States and Canada while exogenous correlation of technology shocks is not important.

In the third chapter, we turn to the sources of business cycles in a closed economy setting and analyzes the effects of news shocks, which are found to be an important driver of business cycles in the U.S. in the recent literature. The innovation of this chapter is that we use data on expectations to inform us about the role of news shocks. This approach exploits the fact that news shocks cause agents to adjust their expectations about the future even when current fundamentals are not affected, therefore, data on expectations are particularly informative about the role of news shocks. Using data on expectations, we estimate a dynamic, stochastic, general equilibrium model that incorporates news shocks for the U.S. between 1955Q1 and 2006Q4. We find that the contribution of news shocks to output is about half of that estimated without data on expectations. The precision of the estimated role of news shocks also greatly improves when data on expectations are used. Moreover, the contribution of news shocks to explaining short run fluctuations is negligible. These results arise because data on expectations show that changes in expectations are not large and do not resemble actual movements of output. Therefore, news shocks cannot be the main driver of business cycles.

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Chapter 1

The Role of Common Shocks in Small Open Economies Between 1900 and 2006

Wataru Miyamoto and Thuy Lan Nguyen

1.1 Introduction

Whether the sources of business cycles are country-specific or common is an important question in the international business cycle literature given its relevance to the policymakers to set domestic and international policies. Nevertheless, the answer for this question has been scarce and inconclusive for small open economies, especially for emerging economies whose data are limited. On one hand, the small open economies literature such as Aguiar and Gopinath (2007) and Garcia-Cicco et al. (2010) has focused entirely on business cycles of individual country, ignoring the possible influence of common shocks to these small open economies. On the other hand, the international business cycle literature on the importance of common shocks such as Kose et al. (2003, 2012) typically finds a small role of common shocks to emerging economies than industrial countries. However, a drawback of this literature which estimates reduced-form dynamic factor models is the lack of interpretation for the estimated common factors and their propagation mechanism in a structural model. Furthermore, their maintained assumption that there is only one common world factor and one group-specific factor can affect their findings as there can be multiple common components driving business cycles.

This paper fills in this gap of the literature by providing a new evidence about the role of common shocks in small open economies in a structural estimation. More specifically, using a new dataset covering 17 small open economies, both emerging and small developed countries, between 1900 and 2006, we estimate a structural small open economy real business cycle model with financial friction where countries are connected with one another through the existence of common shocks. In contrast with the reduced form dynamic factor literature, our structural model allows for several types of structural shocks. In particular, each country is buffeted with five types of shocks, each of which has three components: (i) a world common shock affecting all 17 countries at the same time, (ii) a group-specific shock for countries within small developed and developing group, and (iii) a country-specific shock.

Estimating the model jointly for 17 small open economies using Bayesian methods, we find that common shocks are an important source of fluctuations in these open economies for the last 100 years. In particular, on average, all of the world common and the group-specific shocks explain to about 49% of all output fluctuations over the last century at the annual frequency. The roles of the world common and the group-specific shocks are roughly equal. Common shocks also account for a large fraction of other aggregate variables: 37%, 32% and 40% of the variations in consumption, investment and trade balance, respectively. Additionally, common shocks have heterogeneous effects on these countries. For example, the sign of the effects is positive for Canada, Australia and Argentina while it is negative for Taiwan, Spain and India.

Furthermore, common shocks are important not only for small developed countries like Canada and Australia but also for emerging countries such as Argentina. Common shocks explain roughly 55% of output fluctuations in small developed countries and 45% of that of emerging economies. This result is in contrast with the belief that emerging or developing countries are mostly subject to their country-specific shocks given that these countries suffer from frequent country-specific political and economic reforms. Since emerging economies are more volatile than small developed countries, this variance decomposition suggests that common shocks may have a larger effect in levels in emerging economies than in small developed countries.

Our common shocks are identified through both contemporaneous and dynamic correlations across all country pairs. In the model, since each country is modeled as a small open economy, there is no correlation across countries without common shocks. Therefore, our structural model forces the comovement across all countries to be explained by world common shocks, comovement across countries within each group by group-specific shocks, and the fluctuations independent from other countries by country-specific shocks. This identification implies that common shocks tend to be more important for countries that are more correlated with the rest of the countries in the sample, which is consistent with our findings.

The common shocks identified in our structural estimation capture both worldwide shocks and shocks common to these 17 small open economies coming from large countries. Examples of the worldwide shocks that we capture are important historical episodes such as the Great Depression, the two World Wars and the two oil price shocks. During these episodes, output in all these countries drop in synchronization. Our extracted common shocks can also include shocks from the rest of the world that affect all of the countries in the sample such as U.S. shocks. In particular, we find that world common shocks explain nearly 50% of output fluctuations in Canada, which has a strong tie with the U.S., and these common shocks are highly correlated with U.S. output in the last 100 years. These results suggest that we may capture shocks from large countries such as the U.S. transmitting to all 17 small open economies through financial and trade linkages. It is possible that our common shocks include the shocks originating from one of the 17 countries transmitting to the rest of the countries in the sample, which can overstate the importance of common shocks. However, this component should be small. The reason is that since our sample includes 17 small open economies, shocks originating from Argentina or Canada are unlikely to affect other countries such as Taiwan or India. In other words, taking advantage of the data from small open economies, we can avoid the possible upward bias for our estimates coming from internal propagation among countries in the group.

Our paper further points out the importance of using structural estimation to identify several types of common shocks, which is not done in the existing literature with reduced form dynamic factor estimation approach. In particular, in our structural estimation, we find that not only common productivity shocks but also other types of common shocks such as preference and interest premium common shocks are an important source of business cycle fluctuations for small open economies. When we estimate a standard reduced form dynamic factor model as in Kose et al. (2003) with our new data set, the contribution of common shocks to these small open economies would be much lower, about a *third* of the results obtained in our structural estimation. The reason for this discrepancy is that while there can be multiple types of common shocks in the data, reduced form models often assume that there is only one type of common shocks such as one world common shock and one group-specific shock which can understate the role of common shocks. We demonstrate this problem by two experiments. In the first experiment, we show that the dynamic factor model underestimates the contribution of common shocks when the data generating process has more than one type of common shocks. In the second experiment, the dynamic factor model estimated with the data generated from the data generating process with only one type of common shocks can correctly estimate the importance of common shocks. These experiments illustrate the advantage of structural estimation as we are able to identify several types of common shocks for small open economies using cross equation restrictions that would have been missed otherwise.

Finally, we provide a new evidence about the importance of common shocks over time for the last 100 years. While there are numerous studies on common shocks driving business cycle comovement across countries such as Kose et al. (2003, 2008 and 2012) or Guerron-Quintana (2012), as well as individual country's business cycles like Aguiar and Gopinath (2007), the lack of historical data especially for small open economies has limited the analysis to periods at most after the 1960s, especially for emerging economies. With a new dataset covering 17 emerging and small developed countries for a much longer period, between 1900 and 2006 for not only output, consumption but also investment and trade balance, this paper documents that common shocks are important for small open economies not only in the recent period but also in the first half of the century. In particular, common shocks explain between 55% and 65% of output fluctuations in the period before the 1950s, which is when these small open economies were relatively open in terms of the high trade share in total output. Common shocks are especially important during large worldwide events such as the two World Wars and the Great Depression. Common shocks contribute only about 45% on average to the variations in output for these small open economies between 1950 and 1970, but its role rises again at the beginning of the 1970s when the first oil price shock hit.

Our paper contributes to a vast literature on the determinants of business cycles in small open economies in two ways. First, we focus on the importance of common shocks driving business cycles of small open economies, which has mostly been ignored in the small open economy dynamic stochastic model literature. Second, we provide a new evidence about the type of shocks that are important for these small open economies and decomposing them into common and country-specific components. By pooling the panel of long run data for both emerging economies and small developed countries containing several business cycles[1], we gain estimation efficiency and provide additional evidence about the sources of business cycles in small open economies. Additionally, with regards to the recent debate if trend shocks are the main driver of business cycles in emerging economies but not small developed countries as in Aguiar and Gopinath (2007), we find that stationary productivity shocks are the major source of output fluctuations for emerging countries, which is consistent with the finding for Argentina in Garcia-cicco et al. (2010), and for small developed countries as well. Furthermore, our estimation allows us to decompose the total contribution of trend and

[1]As pointed out in Garcia-Cicco et al. (2010) and Rondeau (2012), long data contain several business cycles, which help identifying the importance of structural shocks such as trend and stationary productivity shocks as drivers of business cycles. Thus, even though there may be structural changes of these economies over the entire 100 years, the fact that short data contain too few business cycles makes long data preferred for estimation.

stationary shocks into common components and country-specific components, which shows that small developed countries are more subject to the world common trend productivity shocks than emerging economies.

This paper is also related to the literature estimating the contribution of common components to business cycles. Unlike prominent works in this literature such as Kose et al. (2003), we adopt a structural estimation, which allows us to identify several sources of common components. Additionally, we have a long run dataset, which helps us to document the pattern of common components over major historical episodes. Some work in the previous literature also use structural model to distinguish the effects of common and country-specific shocks but do not estimate the model such as Glick and Rogoff (1995) and Gregory and Head (1999). These papers, nevertheless, do not have any say in the quantitative importance of common shocks. The paper closest to ours is Guerron-Quintana (2012). However, while he focuses on small developed countries using their quarterly data from 1980, we analyze the importance of common shocks for not only small developed countries but also emerging countries with 100 years of data. Besides, our model features a more realistic debt adjustment cost to proxy for the reduced form financial friction in these countries, as well as a flexible common shock structure to capture the comovement observed in the data. Both of these differences matter for identification and fitness of the model. Finally, an important difference between our paper and Guerron-Quintana (2012) is that we show how the number of common shocks matters for the estimation results obtained from our structural approach compared to the DFM approach.

The rest of the paper is organized as follows: Section 2 documents the main business cycle statistics of small developed and developing countries between 1900 and 2006. Section 3 describes the baseline model. We discuss the estimation method and the identification issues in Section 4. We present the main results of the paper in section 5. In Section 6, we analyze the robustness of our results such as preference specification. Section 7 concludes.

1.2 Business Cycles in Small Open Economies: 1900-2006

This section introduces our novel data set for 17 small open economies and documents the main business cycle statistics for these countries in the last 100 years.

Our new data set includes annual growth rates of output, consumption, investment per capita and trade balance-to-output ratio for 17 small developed and developing countries between 1900 and 2006. The countries are selected based on the availability of the data: they have at least 80 years of data as detailed in Table 1.1[2]. We categorize the countries into two groups based on their present development level, similar to Kose et al. (2011). There are ten developing countries (Argentina, Brazil, Chile, Colombia, India, Mexico, Peru, Taiwan, Turkey and Venezuela) and seven small developed countries (Australia, Canada, Finland, Norway, Portugal, Spain, and Sweden). This grouping helps us characterize the difference between small developed countries and developing countries[3].

Within Country Statistics Some features of our long span data set are similar to the facts documented with shorter data in the literature. First, business cycles in many developing countries are characterized by a more volatile consumption growth rate than output growth rate as shown in Column (1) and (2) of the upper panel of Table 1.2(a). This feature also holds on average across developing countries, shown in the last row of the upper

[2]The data come from several sources such as Barro and Ursua (2008), national statistics offices and historical data publications. More information on the data sources used are available in Online Appendix.

[3]We do not group countries by geographical locations because there are only one or two countries in some regions, which can be a problem when we want to identify the regional shocks.

panel in Table 1.2(a). Second, investment is the most volatile variable in every country in the sample as shown in the column (3) of Table 1.2(a). Third, consistent with standard business cycle facts, consumption and investment are positively correlated with output. Lastly, the trade balance autocorrelation function is downward sloping for all countries as plotted in Figure 1.1, similar to the reported values in Garcia-Cicco et al. (2010). This statistics is one of the important moments in identifying trend and stationary productivity shocks as reported in Garcia-Cicco et al. (2010) and Chang and Fernandez (2010).

Our data set also exhibits several features that are different from the previously documented facts. First, consumption volatility is higher than output volatility in small developed countries, on average. As reported in the first two columns of Table 1.2(a), this fact holds for five out of seven small developed economies. This fact is in contrast with the documented facts in previous studies such as Aguiar and Gopinath (2007), who suggest that the excess volatility of consumption over output is a prominent feature only for developing countries using quarterly data after 1980 but concistent with other studies that use annual data from 1960 such as Chen and Crucini (2011) and Rondeau (2012). Second, trade balance is not procyclical for small developed countries as described in previous papers. There is no strong pattern for trade balance in small developed countries: three out of seven developed countries have countercyclical trade balance as seen in column (8) of Table 1.2(a). Thus, average correlation of output and trade balance across countries is only slightly positive.

Cross Country Statistics Business cycles are correlated across these small open economies for the last 100 years. As shown in Figure 1.2, which plots the output growth rates for all countries in our sample excluding Taiwan[4], output growth rates move in tandem in many periods between 1900 and 2006 such as in the Great Depression and the two World Wars.

[4]Taiwan has a large drop of output growth rate in 1945, which can bias the average in our sample, so we exclude Taiwan from Figure 1.2.

Besides output, consumption, investment and trade balance are also positively correlated across countries as reported in Table 1.2(b), where we take average of the cross country correlation across all pairs of countries. The average correlation of output and consumption may seem low (0.13 and 0.06, respectively). However, as we calculate the cross correlation for each pair of countries, we find that the degrees of correlation vary highly across different pairings of countries. For example, Venezuela and India are negatively correlated or barely correlated with other countries in the sample while Argentina is significantly positively correlated with the rest of the countries (0.19 on average). This explains why on average, the cross correlation is low among developing economies. We note that although many countries in the sample may be quite different with some experiencing default episodes in the last 100 years, developing economies such as those within South America region are correlated with each other significantly, clearly shown in Table 1.2(c) which reports the cross country correlation of output growth rates for each pair of countries. The same is true for consumption growth rates.

Consistent with the international business cycle features, cross country correlations of output are higher than that of consumptions in all pairs of countries. When comparing between small developed and developing countries, we find that cross country correlations of output and consumption are higher for small developed countries than developing countries, which suggests a higher degree of business cycle synchronization among small developed countries than among developing countries. However, investment and trade balance cross country correlations are higher in developing countries than small developed countries. All of these patterns, which are calculated using the data between 1900 and 2006, are true also for the data periods starting after 1945 and 1960. The empirical evidence presented in this section serves as motivation for our focus on the common component driving the business cycles of both small developed and developing countries.

1.3 The Baseline Model

This section presents the baseline model to quantify the contribution of common shocks to small open economies. Our model is a small open real business cycle model with four features. First, we augment the shock structure to include common world and group-specific shocks in addition to country-specific shocks in all of the five structural shocks: trend and stationary productivity, preference, interest rate premium and government spending shocks. Common shocks are the only driver of the comovement across countries i.e. there is no internal propagation of country-specific shocks. This assumption relies on the fact that the size of each country is small, so it is unlikely that a shock from one country such as Canada or Argentina can spillover to the rest of the countries. Even though there are relatively larger countries within one group such as Argentina and Brazil, group-specific shocks have to explain the comovement of all countries including India and Taiwan, which do not trade as much with these countries. Therefore, the bias caused by the shocks propagated by these larger countries within our sample countries may not be significant. We discuss this bias further in the Identification section below. Additionally, we assume that common shocks can have different effects on different countries, similar to Gregory and Head (1999). This assumption is to capture the heterogeneous responses of each country to common shocks.

A second feature of our model is that we allow variable capital utilization in the model to avoid mismeasurement in total factor productivity. Tsyrennikov (2010) documents that in Argentina, capital utilization varies widely in his sample period. Baxter and Farr (2005) also show the importance of variable capital utilization in a two-country model context, where the cross country correlation of productivity shocks is upward biased if there is no variable capital utilization. In our model with annual frequency, when a shock hits the economy, since the capital stock is fixed, it is sensible to allow the level of capital service to adjust. The third feature is investment adjustment cost to allow a smooth response of investment. More specifically, investment adjustment cost is modeled as in Christiano et al. (2005) which is argued to be a reduced form for time-to-build model. Finally, our country interest rate rules following Garcia-cicco et al. (2010) allow us to compare across countries how sensitive their interest rate is to their debt-to-output level, or so-called “financial friction”. We describe below the detailed model for an individual economy, $j \in [1, N]$.

Representative household maximizes the following utility function:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t b_{jt} u(C_{jt}, h_{jt}) \tag{1.1}$$

where b_{jt} is the preference shock of country j at time t, β is the subjective discount factor, C_{jt} is consumption of country j at time t, and h_{jt} is hours worked. In the baseline model, the period utility function $u(C_{jt}, h_{jt})$ is assumed to be the Greenwood, Herkowitz and Hoffman (GHH, 1988) preference, given by:

$$u(C_{jt}, h_{jt}) = \frac{\left[C_{jt} - \psi \frac{1}{\theta} X_{jt-1} \left(h_{jt}\right)^{\theta}\right]^{1-\sigma} - 1}{1-\sigma}, \tag{1.2}$$

where $\theta > 0$ determines the Frisch elasticity of labor supply, which is $\frac{1}{\theta-1}$, $\psi > 0$ is a scale parameter, and X_{jt} is the trend component in the production function to induce stationarity. This GHH preference has been used widely in the small open economy literature (Mendoza 1991, Garcia-Cicco et al. 2010, among others) since it can generate trade balance countercyclicality and avoid the case where hours fall in response to a rise in trend productivity due to wealth effect. We later show that our main results do not change if we use the standard preference specification proposed by King, Plosser and Rebelo (1988).

The representative household faces the following period-by-period budget constraint:

$$\frac{D_{jt+1}}{R_{jt}} \geq D_{jt} - Y_{jt} + C_{jt} + G_{jt} + I_{jt} + \widetilde{a}\left(u_{jt}\right) K_{jt}, \tag{1.3}$$

where D_{jt+1} is the stock of debts chosen at time t, and R_t denotes the interest rate on bonds held between period t and $t+1$, Y_{jt} is the total output, G_{jt} is the government spending which is exogenously determined, I_{jt} is the total investment and $\widetilde{a}\left(u_{jt}\right)$ is the utilization cost. We assume the utilization cost has a following functional form:

$$\widetilde{a}\left(u_{jt}\right) = \left[a_{1j}\left(u_{jt} - 1\right) + \frac{1}{2} a_{2j}\left(u_{jt} - 1\right)^2\right].$$

Following Christiano et al. (2005), capital stock evolves according to the following law of motion:

$$K_{jt+1} = \left(1 - \delta\ \right) K_{jt} + I_{jt}\left[1 - \frac{s_j}{2}\left(\frac{I_{jt}}{I_{jt-1}} - \mu_{ss}^j\right)^2\right], \tag{1.4}$$

where $s_j > 0$ is a parameter for the investment adjustment cost, δ is the depreciation rate of capital, μ_{ss}^j is the steady state investment growth rate. Each economy is also subject to country premium interest rate shocks. The interest rate, R_{jt}, that country j faces is then given by:

$$R_{jt} = R_{j,ss} \exp\left[\phi_j\left(\frac{\frac{D_{jt+1}}{X_{jt}}}{y_{j,ss}} - \frac{d_{j,ss}}{y_{j,ss}}\right)\right] pm_{jt}, \tag{1.5}$$

where $R_{j,ss}$ is the steady state interest rate of country j, ϕ_j is a parameter governing the financial friction that country j has, $y_{j,ss}$ and $d_{j,ss}$ are the stationary detrended output and bond holding level of country j, respectively, and pm_{jt} is the interest rate premium shock. In this specification, interest rate is sensitive to the debt-to-output level relative to its steady state through ϕ_j. The higher ϕ_j is, the more interest rate adjusts with respect to the amount of debt that country j holds, i.e. when debt over steady state output ratio changes by 1%, interest rate changes by $\phi_j\%$. This is the "financial friction" in our model. Unlike many papers in the literature which assign ϕ_j to be small only to induce stationarity for the model such as Aguiar and Gopinath (2007) and Guerron-Quintana (2012), we estimate this parameter, which allows us to compare the relative lending and borrowing costs that these countries are facing.

The representative household maximizes the expected lifetime utility subject to the budget constraint above and a no-Ponzi condition:

$$\lim_{h\to\infty} E_t \frac{D_{jt+h}}{\Pi_{s=0}^{h} R_{js}} \leq 0. \tag{1.6}$$

The production function takes a standard Cobb-Douglas form:

$$Y_{jt} = a_{jt} \left(u_{jt} K_{jt}\right)^{\alpha} \left(X_{jt} h_{jt}\right)^{1-\alpha}, \tag{1.7}$$

where a_{jt} and X_{jt} are the transitory and trend productivity shocks, respectively.

We follow Gregory and Head (1999) to assume that each type of the structural shocks consists of world common, group specific and country-specific shocks. More specifically, the stationary productivity shock process in country j has three components: a world common shock that affects all countries, a_t^c, a developed (developing) group-specific shock, a_t^g, that affects only countries within the same developed (developing) group, and a country-specific shock a_t^j. The law of motion for stationary productivity shocks is then described by:

$$a_{jt} = \left(a_t^c\right)^{v^{acj}} \left(a_t^g\right)^{v^{agj}} a_t^j. \tag{1.8}$$

The world common shock and group-specific shock can affect the economies differentially, which is captured by the parameters v^{acj} and v^{agj}, respectively. In our model, we restrict the sign of v to be positive for one country to facilitate identification. We can interpret v's as the responsiveness of the fundamentals in each country to common shocks. There are several reasons for why v's are left unrestricted. First, it is possible that a good shock for one country can be a bad shock for another country. An example of such shock is the oil price shock which can have opposite impacts on oil importing and exporting countries. Also, when we look at each country's correlation with the rest of the countries in the data set, there are some countries such as India which are negatively correlated with other countries. Another reason for the unrestricted v's is to keep the specification same as the dynamic factor model (DFM) approach in the sense that that there is a factor structure to the structural shocks, facilitating our comparison with the reduced-form literature. Lastly, though not reporting here, we actually estimate a version of the model in which common shocks must affect all countries in the same manner, i.e. $v = 1$ for all countries and common shocks and find that the estimated model cannot capture the cross country correlation. All common and country-specific shocks follow AR(1) processes, given by:

$$\log a_t^c = \rho_{a^c} \log a_{t-1}^c + \varepsilon_{a^c,t},\ \varepsilon_{a^c,t} \sim N(0,1) \tag{1.9}$$

$$\log a_t^g = \rho_{a^g} \log a_{t-1}^g + \varepsilon_{a^g,t},\ \varepsilon_{a^g,t} \sim N(0,1) \tag{1.10}$$

$$\log a_t^j = \rho_{a^j} \log a_{t-1}^j + \varepsilon_{a^j,t},\ \varepsilon_{a^j,t} \sim N(0,\sigma_{aj}^2). \tag{1.11}$$

The natural logarithm of the trend productivity shocks X_{jt} is assumed to follow:

$$\log X_{jt} = \log X_{jt-1} + \log \mu_{jt}. \tag{1.12}$$

Similar to the stationary productivity shock process, the natural logarithm of the gross growth rate of X_{jt}, denoted by μ_{jt} is a stationary AR process, with three components: world common shocks μ_t^c, group-specific shocks μ_t^g and country specific shocks μ_t^j which can have differential effects on each of the economies through $v^{\mu ij}$ for $i = c, g$. Therefore, the stochastic trend productivity shock process can be described by the following equations:

$$\begin{aligned}
\mu_{jt} &= (\mu_t^c)^{v^{\mu cj}} (\mu_t^g)^{v^{\mu gj}} \mu_t^j && (1.13)\\
\log \mu_t^c &= \rho_{\mu^c} \log \mu_{t-1}^c + \varepsilon_{\mu^c,t},\ \ \varepsilon_{\mu^c,t} \sim N(0,1) && (1.14)\\
\log \mu_t^g &= \rho_{\mu^g} \log \mu_{t-1}^g + \varepsilon_{\mu^g,t},\ \varepsilon_{\mu^g,t} \sim N(0,1) && (1.15)\\
\log \left(\mu_t^j/\mu_{ss}^j\right) &= \rho_{\mu^j} \log \left(\mu_{t-1}^j/\mu_{ss}^j\right) + \varepsilon_{\mu^j,t},\ \varepsilon_{\mu^j,t} \sim N(0,\sigma_{\mu j}^2). && (1.16)
\end{aligned}$$

The economy also faces a country premium interest rate shock, which is a combination of a world common shock, pm_t^c, a group-specific shock, pm_t^g, and a country specific shock, pm_t^j. The stochastic process for a country interest rate is described by:

$$\begin{aligned}
pm_{jt} &= (pm_t^c)^{v^{pmcj}} (pm_t^g)^{v^{pmg}j} pm_t^j && (1.17)\\
\log pm_t^c &= \rho_{pm^c} \log pm_{t-1}^c + \varepsilon_{pm^c,t},\ \ \varepsilon_{pm^c,t} \sim N(0,1) && (1.18)\\
\log pm_t^g &= \rho_{pm^g} \log pm_{t-1}^g + \varepsilon_{pm^g,t},\ \ \varepsilon_{pm^g,t} \sim N(0,1) && (1.19)\\
\log pm_t^j &= \rho_{pm^j} \log pm_{t-1}^j + \varepsilon_{pm^j,t},\ \ \varepsilon_{pm^j,t} \sim N(0,\sigma_{pmj}^2). && (1.20)
\end{aligned}$$

We can interpret the world common interest rate premium shock as world or US interest rate shocks that follow an AR(1) process. Similarly, a positive group-specific premium shocks, such as for developing group, can be interpreted as an increase in the interest rate that developing countries face due to some events related to this specific group.

Government spending, G_{jt}, is assumed to have the same stochastic trend as output. The log deviations of spending from trend $g_{jt} = \frac{G_{kt}}{X_{jt}}$ is assumed to have three components: world common, group specific and country specific components, each of which follows an AR(1) process:

$$\begin{aligned}
g_{jt} &= \left(g_t^c\right)^{v^{gcj}} \left(g_t^g\right)^{v^{ggj}} g_t^j && (1.21)\\
\log g_t^c &= \rho_{g^c} \log g_{t-1}^c + \varepsilon_{g^c,t},\ \ \varepsilon_{g^c,t} \sim N(0,1) && (1.22)\\
\log g_t^g &= \rho_{g^g} \log g_{t-1}^g + \varepsilon_{g^g,t},\ \varepsilon_{g^g,t} \sim N(0,1) && (1.23)\\
\log\left(g_{jt}/g_{ss}^j\right) &= \rho_g^j \log\left(g_{jt-1}/g_{ss}^j\right) + \varepsilon_{g^j,t},\ \ \varepsilon_{g^j,t} \sim N(0,\sigma_{gj}^2). && (1.24)
\end{aligned}$$

Lastly, similar to the shocks described above, the stochastic processes of preference shocks is given by the following equations:

$$\begin{aligned}
b_{jt} &= \left(b_t^c\right)^{v^{bcj}} \left(b_t^g\right)^{v^{bgj}} b_t^j && (1.25)\\
\log b_t^c &= \rho_{b^c} \log b_{t-1}^c + \varepsilon_{b^c,t},\ \ \varepsilon_{b^c,t} \sim N(0,1) && (1.26)\\
\log b_t^g &= \rho_{b^g} \log b_{t-1}^g + \varepsilon_{b^g,t},\ \varepsilon_{b^g,t} \sim N(0,1) && (1.27)\\
\log b_{jt} &= \rho_b^j \log b_{jt-1} + \varepsilon_{b^j,t},\ \varepsilon_{b^j,t} \sim N(0,\sigma_{bj}^2). && (1.28)
\end{aligned}$$

where we can think of the common preference shocks as common demand shocks.

1.4 Estimating Common shocks

In this section, we discuss our estimation and identification strategy for the baseline model. We first explain calibrated parameters, followed by the Bayesian estimation method and its estimated parameter with the model fit. We also discuss the identification for the model.

1.4.1 Calibrated Parameters

Table 1.3 reports the values of calibrated parameters common for all countries, following the calibration strategy in Garcia-Cicco et al. (2010). We set the risk aversion parameter σ to be 2 and capital share α to be 0.32. Labor elasticity parameter θ is set to be 1.6 as frequently used in the literature such as Mendoza (1994), Neumeyer and Perri (2005), and Garcia-Cicco et al. (2010). The discount rate β is set to be 0.9224. Since we do not have government spending series going back to 1900, government spending share in output, G/Y, is set to match the average government spending share for each country available between 1960 and 2006. We set the steady state level of debt d_{ss} to match the average trade balance-output ratio, and the depreciation rate δ to match the average investment-output ratio in the data for each country. The parameter related to labor supply, ψ, is set so that the steady state level of hours h is equal to 1. We also set the steady state growth rate, μ, equal to the average output growth rate for each country in the data. Since v's and the standard deviations of the shocks are not identified separately, we normalize the standard deviation of all common shocks to be 1 and estimate the effects of the shocks in each country through v's. Also, we assume positive v in one of the countries in the same group to identify the sign of the shock. The rest of the parameters are estimated.

1.4.2 Bayesian Estimation

We estimate the model using the Metropolis-Hasting procedure accommodating missing data. We draw from the posterior distribution of estimated parameters, denoted as Θ, given the sample data matrix Y. This requires the evaluation of the product of likelihood function and prior distribution, which is denoted as $L\left(Y|\Theta\right)P\left(\Theta\right)$. To evaluate the likelihood function $L\left(Y|\Theta\right)$ numerically, we first solve the model using the first order approximation method in

Schmitt-Grohé and Uribe (2004) and obtain the following state space form.

$$\begin{aligned} X_{t+1} &= h_x(\Theta) X_t + \eta(\Theta) \varepsilon_t \\ obs_t &= g_x(\Theta) X_t, \end{aligned}$$

where X_t is a vector of state variables and ε_t is a vector of structural shocks with $N(0, I)$ and obs_t are the observables. We have four variables for each country: $[\Delta GDP_t, \Delta C_t, \Delta I_t, TBY_t]$, where Δ denotes first difference in log, resulting in 68 observables in total. We numerically evaluate the likelihood function $L(Y|\Theta)$ by applying the Kalman filter to this state space form. Evaluating prior distribution $P(\Theta)$ is straightforward since we use known distributions as described below.

The first columns of Table 1.5(a) and Table 1.5(b) report our prior distributions for the estimated parameters. We take a conservative stance and impose flat priors following previous literature such as Garcia-Cicco et al. (2010). We set priors for the parameters governing the investment adjustment cost, s_j, to be Gamma distribution $G(0.5, 0.5)$. We define the utilization cost, ucost, as $\frac{1-\text{ucost}}{\text{ucost}} = \frac{a_2}{a_1}$. When the utilization cost is close to 1, it is extremely costly to change capital utilization, as a result, capital utilization remains constant. In contrast, when ucost$=0$, the marginal cost of changing capital utilization is constant. Following Smets and Wouters (2007), we impose a Beta prior distribution for capital utilization, $B(0.5, 0.15)$. Since there is no evidence on the debt adjustment cost parameters, ϕ_j, we choose a Gamma distribution with fairly large standard deviation $G(5, 3)$. The priors of all the autocorrelation coefficients of shocks have a Beta prior $B(0.5, 0.2)$. Lastly, we assume uniform distribution for standard deviations of all shocks and the common shocks' effect on individual countries, v's. Overall, we have 406 parameters to estimate given 68 observables.

Our baseline estimation does not include measurement errors to reduce the number of parameters to the minimum. Although historical data are subject to measurement error problem, especially for developing countries, there are two reasons for us to estimate the model with long data without measurement errors. First, as argued in Garcia-Cicco et al. (2010) and Rondeau (2012), long data are helpful for identification of trend shocks as they contain several business cycles over time. Therefore, the long data set helps us to understand the driving forces of business cycles in developing countries which has been limited in the literature. Second, as long as measurement errors are independent across countries, which is sensible given the fact that data come from several different sources, we expect that the role of common shock is rather underestimated. In other words, by omitting the measurement errors, we obtain a lower bound of the importance of common shocks. We check in the Robustness section how calibrating the model with measurement errors may change the results.

1.4.3 Estimated Parameters and Model Fit

The estimated parameters are presented in Table 1.5(a) and 1.5(b) for all 17 countries, calculated from four chains of 200,000 draws. We first highlight the following features: First, the estimated country-specific deep parameters such as financial friction parameter and investment adjustment cost vary widely across countries, reflecting the structural heterogeneity of the countries within the sample. Second, the debt adjustment cost parameter, ϕ_j, is significantly different from 0 for all countries, implying a non-trivial debt adjustment cost that both developing and small developed countries face. This finding provides a new evidence for the financial frictions in small developed countries. Nevertheless, debt adjustment cost is smaller for small developed (0.9) than developing countries (2.1) on average, which lends support to the hypothesis that developing countries face larger financial frictions than small developed countries. Within each group of countries, the degree of financial friction also varies. For example, among developing countries, Venezuela, Peru and Taiwan have a relatively low ϕ, less than 0.65 and among small developed countries, ϕ's in Sweden, Norway and Canada are the smallest. Third, the utilization cost are significantly lower than 1 in all countries, meaning that countries are able to adjust their utilization of capital in response to shocks, so adding utilization cost in our model helps to avoid overstating the role of productivity shocks.

Table 1.6 reports the theoretical second moments and their empirical counterparts. Not only can the model match the average standard deviation of output quite well but it can also generate the excess volatilities of consumption and investment compared to output especially for developing countries. For example, our model can also generate both countercyclicality and the autocorrelation of trade balance of developing countries, which are the two features that have been emphasized as important in identifying trend and stationary productivity shocks in the literature. Moreover, our baseline model can match many cross country correlations. The last row of Table 1.6 shows that average cross country output and consumption correlations implied by the model are close to the data. Even for each country pairs, our model are also able to match closely the cross correlation across countries.

Finally, our baseline specification is preferred by the data compared to a restricted version where common shocks have the same effect on all countries, i.e. $v = 1$ for $\forall j$[5]. As expected, the restricted version is far worse than the baseline model, unable to generate the correlation across country as seen in the data. Furthermore, the log marginal likelihood of the restricted model is much lower than that of the baseline. Overall, we find that the data support our full model.

[5] Results for the case $v = 1$ are available upon request.

1.4.4 Identification

This section discusses how our estimation approach identifies common shocks as well as different types of shocks in the model. First, our full information estimation uses all moments of the long data such as the persistence of output and consumption growth rates to separate trend from stationary productivity shock. This identification scheme is different from the identification in Aguiar and Gopinath (2007), which is based on the households' consumption smoothing behavior when there is no financial frictions. In their identification, households can borrow and lend in international markets to smooth consumption in response to trend productivity shocks, causing trade balance to be countercyclical. The excess volatility of consumption to output in the data is then explained by the persistence of trend productivity shocks. On the other hand, in our model, that identification may not hold because of the debt adjustment cost ϕ_j, which is interpreted as the degree of "financial frictions," which is closely related to the behavior of the autocorrelation function of trade balance. When this parameter value is very small, trade balance is near random walk. However, as shown in Figure 1.1, the autocorrelation function of trade balance is steeply downward sloping for all countries. Therefore, ϕ_j is estimated to be larger than the value set in the literature for both small developed and developing countries. The high value of ϕ_j means that borrowing and lending are costly in international market, implying that households cannot smooth consumption easily by borrowing internationally even under trend productivity shocks. In this case, trade balance as well as the growth rates of output and consumption are important to identify the trend and stationary productivity shocks, which also justifies our use of the long data as stressed by both Garcia-Cicco et al. (2010) and Rondeau (2012).

The rest of the shocks are identified as follows. Preference shocks, which represent demand shocks, are to explain the highly volatile consumption in these countries. In the economy where households cannot borrow or lend abroad easily, trade balance does not respond much to productivity shocks, which changes the wealth of the country, country premium shock is necessary to explain trade balance movement. In other words, preference and interest rate premium shocks are necessary to explain excess volatility of consumption and the movements of trade balance. This feature where domestic and trade variables explained by different types of shocks are also present in the literature such as Justiniano and Preston (2008) and Adolfson et al. (2007). Finally, government spending and preference shocks can be separately identified as government spending is closely related to the resource constraint, in which the other four components are observed. Besides, preference shocks increase consumption while government spending shocks do not, which help us to distinguish these two shocks.

Second, common shocks are identified through both contemporaneous and dynamic correlations across all country pairs. Theoretically, since these countries are modeled as small open economies, there is no correlation across countries if there is no common shocks. Thus, our structural model forces the comovement in aggregate variables across all countries to be explained by world common shocks, and the comovement across countries within each group by group-specific shocks. On the contrary, the country-specific shocks are to explain the movements in aggregate variables in each country that are independent from the rest of the countries. This identification scheme suggests that countries more correlated with the rest of the countries on average tend to have a higher contribution of common shocks, which is true in our results below. Additionally, since we estimate the model pooling the data for all 17 countries, we increase the precision of the estimates, especially for the common components, compared to individual country estimation in the existing literature.

1.5 The Importance of Common Shocks in Small Open Economies: 1900-2006

In this section, we discuss what our estimated common shocks capture and their role in driving business cycle fluctuations in small open economies between 1900 and 2006, highlighting the difference between small developed and developing countries as well as between our approach and the reduced form dynamic factor model approach in the previous literature.

1.5.1 What Are Common Shocks?

Common shocks in our estimation capture three components: worldwide shocks, shocks common to all countries in the sample coming from large countries as well as shocks common to countries in the sample only.

To show that our estimated common shocks contain worldwide shocks, Figure 1.3 plots the extracted world common shocks calculated using the parameters at posterior mean. Our common shocks capture major historical events. The extracted world shocks include the Great Depression, the two World Wars and the two oil price shocks. These events appear as large persistent common productivity shocks to all economies, causing output to fall in tandem. For example, World War II is associated with a negative world trend productivity shock, but an increase in productivity right after suggests the recoveries of the world economy. The world common government spending shocks capture the common policies across countries such as the increase in spending during World War II, followed by a spending cut at the end of the war.

To gauge the extent to which our extracted common shocks also include shocks that are from large countries outside of the sample, we also plot in Figure 1.3 the extracted common shocks alongside with the US output growth rate, which proxies for the US shocks. The correlation of the world trend and stationary productivity shocks with the US output growth are 0.32 and 0.26, respectively. Also, the world preference shock is negatively correlated with the US output growth (-0.37). Additionally, the world common shocks explain a large fraction, up to a half, of Canadian output fluctuations. These results suggest that even though we do not include large countries in our data set, the extracted common shocks may also capture shocks coming from the U.S. and Europe that are transmitted to these countries through international trade and financial linkages.

Our common shocks can certainly contain shocks common to countries within our sample only, but we argue that this component should be small. The reason is as follows: Our sample includes 17 countries in many different parts of the world. The sizes of these countries are also small, meaning that it is unlikely there are some type of shocks that affect India and Peru but not any other countries outside of the sample. Finally, it is possible that an idiosyncratic shock in Argentina may affect the rest of the countries, such as Brazil, through their international linkages, causing an upward bias in our estimates for the role of common shocks. However, these idiosyncratic shocks should be negligible in our estimated common shocks. One reason is that all of these countries are small open economies in different regions of the world. Therefore, an idiosyncratic shock in Argentina is unlikely to affect other 16 countries significantly through trade when Argentina is not the major trading partner with many countries in the sample. In our estimation results, both world common and group-specific shocks are important not only for certain pairs of countries such as Argentina and Brazil but for other countries also. Additionally, as plotted in Figure 1.4 the historical decomposition of output in Argentina (upper panel) and Canada (lower panel), the 2002 Argentina crisis is captured in our estimation as country-specific. In other words, the possible bias caused by the propagation of country-specific shocks within our sample may not be problematic in our case.

1.5.2 The Contribution of Common Shocks

Although the effects of common shocks are heterogeneous across countries, both world common and group-specific shocks are a non-negligible source of fluctuations in these countries. On average, 49% of the fluctuation in output, 37% in consumption, 32% in investment, and 40% in trade balance between 1900 and 2006 can be attributed to all types of common shocks, as reported in the last row of Table 1.7. We find that both world common and group-specific shocks play similar roles in explaining these small open economies. For example, about 25% of output fluctuations are explained by world common shocks. This result reflects the substantial comovement of these countries during major historical episodes such as the Great Depression which are captured in the extracted world common shocks. Besides, as common shocks have to explain both static and dynamic correlations across countries, there is a positive relationship between the cross country correlation and the contribution of common shocks as plotted in Figure 1.5 for the output growth rate.

Contribution of Common Shocks Over time The importance of common shocks in terms of explaining business cycles in small open economies fluctuates across the 100 year timespan. Figure 1.6 plots a 20-year window rolling over contribution of common shocks to output fluctuations across 17 countries between 1900 and 2006. Before 1945, the contribution of the world common and group-specific shocks increased gradually, explaining about 50% of output fluctuations on average. By the 1940-1945 period, common shocks explain up to 60% of the output volatilities on average. This increase in importance of common shocks is due to a substantial increase in the presence of world common shocks, which supports the argument that there were large disaster shocks propagating strongly to all countries in the world, causing output to fall in tandem. Between 1950 and 1970, the importance of common shocks decreased, explaining roughly 40% of output on average. However, the role of common shocks began to rise again beginning from the 1970s when oil price shocks, which are captured as world common shocks, hit all the countries as they became more integrated with each other. These variations in the importance of common shocks are driven mostly by the changes in the world common shocks' contribution, as shown in the second panel of Figure 1.6. In fact, group-specific shocks explain roughly 25% of the total output variations on average, and only slightly over 28% after the 1990s. This result is consistent with Kose et al. (2012), who find an increasing importance of group-specific shocks in recent period after the 1990s.

The variations in the importance of common shocks over time are positively correlated with the level of openness of the countries in the sample. We proxy the level of openness by the total value of trade over output, as plotted in Figure 1.7. Although the degree of openness varies widely across countries, on average, countries were less open during the 1950-1970 period, which coincides with the time when the role of common shocks are smaller. This result suggests that international trade and financial linkages may explain why some countries are more driven by outside shocks than others. Therefore, one can expect large shocks such as the Great Recession to play a significant role in the drop in economic activities in these countries as countries are more integrated[6].

Types of Common Shocks There are several types of common shocks important for business cycles in small open economies. In particular, productivity shocks are the most important type of common shocks for output. On average, common stationary productivity shocks (28%) are more important than trend productivity shocks (17%). This finding is consistent with Guerron-Quintana (2012), who finds the same pattern for small developed countries with quarterly data after 1980. Consumption volatilities are explained by not only common productivity shocks but also common preference shocks, each of which accounts for

[6]Ideally, we should include 2006-2012 data. However, as we started our research in 2009, we did not have access to the data after 2007 for many of the countries in the sample.

a large fraction of consumption volatility. The reason for this result is as follows. When debt adjustment cost ϕ_j is high, the excess volatility of consumption relative to output is explained by preference shocks. As consumption are correlated across countries, the estimation assigns a significant role to common preference shocks.

Common interest rate premium and spending shocks do not explain much of the movements in output and consumptions, but account for a sizable fraction of investment and trade balance. For example, world common and group-specific interest rate premium shocks together account for over 20% of the trade balance variations and 12% of investment. The reason for why common interest rate premium shocks are important to explain the behavior of trade balance is that when households are not able to lend and borrow internationally, i.e. ϕ_j is large, interest rate premium shocks have to explain the quick tapering off autocorrelation function of trade balance. Since trade balance is correlated across countries, the role of common interest rate premium shocks are non-negligible. These results suggest the importance of ϕ_j in our estimation, similar to Garcia-cicco et al. (2010). Additionally, the fact that different types of shocks explain the comovement of different aggregate variables is consistent with other papers in the small open economy literature like Adolfson et al. (2007), Justiniano and Preston (2008) and Garcia-cicco et al. (2010). We show later how this result is important to understand the difference between our structural approach and the reduced form dynamic factor model approach.

1.5.3 Small Developed vs Developing Countries

Common shocks are important not only for small developed countries but also for developing countries. We report in Table 1.7 the fractions of the variations in output, consumption, investment and trade balance explained by common shocks for small developed and developing countries on average. On average, common shocks are an important driver of business cycles in small developed countries. For example, common shocks explain about 55% of output fluctuations in small developed, which is sensible because these developed countries are likely to be integrated and subject to common shocks. Although common shocks are less important for developing countries than small developed countries, they still contribute to nearly a half of business cycle fluctuations in developing countries, explaining around 45% and 42% of output and consumption, respectively. The fact that developing countries are more volatile than small developed countries, the high contribution of common shocks in the variance decomposition implies a significant effect in the *level* to these developing economies. As plotted in Figure 1.4, the historical decomposition exercise shows that a sizable fraction of business cycles in Argentina, for example, is explained by common shocks even though country-specific shocks such as the 2002 crisis explain their large fluctuations. Especially in the first half of the century, the drops in Argentine output in the 1910s and early 1930s are largely driven by important world common shocks.

Business cycles in small developed and developing countries are driven by different types of common productivity shocks. In particular, we find that common trend productivity shocks are more important than common stationary productivity shocks in small developed countries, and the reverse is true for developing countries. We can interpret this result as follows: Developed countries are generally closer to the world technology frontier, so they are more subject to common trend technology shocks. However, in developing countries, there are many policy and structural reforms, so the trend productivity shocks that are important for them are country-specific and not common trend, which is what we find in our estimation.

Another important finding which is a byproduct of our estimation is that country-specific stationary productivity shocks are more important than country-specific trend productivity shocks in both small developed and developing countries, on average. For example, only 7% of Argentine output fluctuations is explained by country-specific trend productivity shocks while nearly 41% explained by country-specific stationary shocks. Similarly, 3% of Spanish output fluctuations is explained by trend compared to 66% by stationary productivity shocks. Nevertheless, the importance of trend versus stationary productivity shocks are heterogeneous within each group of countries: In four out of ten developing countries and in three out of seven small developed countries, trend productivity shocks dominate stationary productivity shock. In other words, the importance of trend versus stationary productivity shocks in Aguiar and Gopinath (2007) and Garcia-cicco et al. (2010) is not conclusive for each group of countries even though on average, the total contribution of common and country-specific trend and that of stationary productivity shocks for each group support the result in Garcia-cicco et al. (2010): trend is not the cycle.

Finally, investment and trade balance in small developed countries are more subject to common country premium shocks than those in developing economies. For example, while world premium shocks explain 12% of trade balance in small developed countries on average, they are only able to account for 4.4% of trade balance in developing countries. A possible reason for this result is that developing countries often face highly volatile country premium. Therefore, country-specific shocks should be more important in these countries than small developed countries.

1.6 Structural Estimation and the Reduced Form Dynamic Factor Model (DFM) Estimation

This section discusses how our results depend on the choice of estimation methods. In particular, we compare the structural estimation method with the dynamic factor model (DFM) estimation method often used in the international business cycle literature such as Kose et al. (2003, 2012). We also show that the DFM approach can underestimate the importance of common shocks when there are multiple common shocks driving the comovement across countries.

To understand if estimation approaches can affect the estimated role of common shocks, we apply the reduced form dynamic factor model (DFM) approach using our dataset. The DFM estimation approach is common in the literature on how common factors or shocks drive business cycle comovement pioneered by Kose et al. (2003). In these papers, except for Mumtaz et al. (2011) who attribute more than 50% of output fluctuations to common shocks in an estimation for 36 countries after 1984 using output and inflation, other papers such as Kose at al. (2003, 2012) find a much limited role of common shocks to small open economies, explaining less than 20% of output fluctuations. Since we estimate the structural model using a new data set, we estimate the role of common shocks using the DFM approach for the same data. In particular, the DFM model assumes that each of the four variables, y_{it}, in country i at time t can be decomposed into four components: a world common factor that affects all four variables of all 17 countries, a group-specific factor that affects only those within the same group, a country-specific factor which is only relevant within a country, and an idiosyncratic component which is specific to each variable only:

$$y_{it} = a_i + b_i^{world} f_t^{world} + b_i^{group} f_t^{group} + b_i^{country} f_t^{country} + \varepsilon_{it}. \tag{1.29}$$

All common factors, f_t^{world}, f_t^{group}, $f_t^{country}$ and the idiosyncratic component ε_t, are assumed to follow an AR(1) process.[7] As reported in Column 1 of Table 1.8, the mean contribution of world and group shocks is roughly 16% of output fluctuation compared to 49% in our structural estimation. The discrepancies are also large for other variables. For example, 14% of consumption variation is attributed to common factors compared to 37% in our

[7]The results do not change if we set more number of lags for the AR processes.

baseline estimation. In other words, the results obtained from the DFM estimation are much lower than those from our structural estimation.

Our intuition for the discrepancies between the two approaches is as follows: In the DFM approach employed in the common shock literature, there are typically only one common world factor, one common group factor and one country specific factor. In other words, there is only one common factor at each grouping level, for a total of two common factors for each country. On the other hand, there may be more than one type of common shocks that can affect business cycle comovement across countries. In our estimation, we find that there are a total of 10 types of common shocks and each type of common shocks has a role in explaining the data. This difference in the number of common shocks assumed in the two approaches may explain why the DFM estimation results are different from those of structural estimation.

To demonstrate our intuition that the DFM approach may not be able to correctly estimate the role of common shocks if the data generating process has more than the number of factors assumed in the estimation, we conduct two counter factual exercises. In the first experiment, we apply the DFM approach to estimate the role of common shocks in an artificial data set. The artificial data are generated from our estimated structural model, which has multiple common shocks. We find that the contribution of common shocks obtained from the DFM approach is less than 20% for output while in the data generating process, the contribution of common shocks to output is close to 50%. In the second experiment, we generate artificial data from our baseline model where all but *one* world common shock and one group-specific common shock are shut down. In particular, we keep world common, group-specific and country-specific stationary productivity shocks since they are important for output and consumption. We then estimate the contribution of common shocks with the DFM approach on this generated data set. The results in Columns 2 and 3 of Table

1.8 show that the DFM estimates are close to the actual contribution of common shocks to all of the variables, suggesting that the DFM approach works reasonably well when the data generating process has only one type of common shocks as in the assumption of the DFM. These two counter factual exercises demonstrate that the number of common shocks assumed in the estimation process matters for the results. One support for the existence of multiple factors in our data is that the principle component analysis shows that the first component explains about 25% while each of the next four components explain between 6% and 9% of the data. The lesson coming out of our experiment is that one should be cautious when assuming the number of common factors when conducting dynamic factor estimation.

1.7 Robustness Check

In this section, we discuss the robustness of our results with respect to different data periods, measurement errors in the estimation, and different preference specification.

1.7.1 Subperiod Data

In our baseline model, we calibrate government spending share in the steady state using available data after 1960. Therefore, we may overstate the share in the first half of the twentieth century. To check if this possibility can lead to a bias in our estimation, we break the data at 1960 and reestimate the model using the steady states specific for each period. For example, we set $\frac{G}{Y}$ to be 0.1 for all countries between 1900-1960 as Garcia-Cicco et al. (2010), and the corresponding steady state using our available data for the 1960-2006 period. Other calibrated parameters are the same as in the baseline estimation.

The results for the two subperiods are shown in Table 1.9 along side with those from the baseline estimation. Common shocks are important for both periods, explaining over 50% of output fluctuations. Furthermore, consistent with our baseline model, the role of common shocks is the largest for output, then trade balance, consumption and investment. Moreover, the pattern of common shock contribution over time is similar as our baseline model where common shocks are more important in the first half of the century than in the second half. Lastly, it remains true that while common productivity shocks explain the most variation of output and consumption among all the common shocks, common premium and preference shocks are important for investment and trade balance.

1.7.2 Measurement Errors

In our baseline estimation, although we do not include measurement errors for the observables, which arguably problematic since long data certainly contain measurement errors, we argue that our estimates for the role of common shocks are not upward-biased. First, as long as measurement errors are independent across countries, our estimation should not overstate the role of common shocks. Second, to partially address measurement errors in the observables, we re-estimate our model with calibrated measurement errors. More specifically, the state space form of the model is now

$$
\begin{aligned}
X_{t+1} &= h_x(\Theta) X_t + \eta(\Theta)\varepsilon_t \\
observables_t &= g_x(\Theta) X_t + me_t,
\end{aligned}
$$

where me_t denotes the measurement error for each observables at time t. Since there are already 406 estimated parameters, we do not estimate these measurement errors. Instead, we calibrate the measurement errors as follows. First, we estimate the measurement errors and other parameters of the baseline model using the Bayesian methods for each country individually, i.e. there are no common shocks. Following Garcia-Cicco et. al. (2010), the measurement errors were restricted to be no more than 5% of the variance of the corresponding observable. Then, we set the measurement errors in the baseline model with common shocks using the estimated measurement errors from the first step. We finally re-estimate the 406 parameters of the baseline model as described above.

The variance decomposition of the model with measurement errors averaged across countries is given in Table 1.10. For ease of comparison, we also report the baseline model (GHH columns). Although the average contributions of common shocks in models with and without measurement errors are not exactly the same, we find that our main conclusions above do not change. First, common shocks explain a large portion of the variations in output, consumption, investment and trade balance. In fact, the contribution is slightly higher in the model with measurement errors than in the baseline model, especially for trade balance. Second, even in the estimation with measurement errors, we find that there are multiple common shocks explaining the behavior of the variables for all 17 countries. Third, when we plot the common shock contribution over time obtained from the estimation with measurement errors, we find a similar pattern as in the baseline model: common shocks are more important before the 1950s and after the 1970s. Lastly, it remains true that the most important world common shock for developing countries is stationary productivity shock and for small developed countries is trend productivity shocks. In other words, our baseline estimates are robust even if we allow for measurement errors in the estimation procedure.

1.7.3 Preference Specification

Finally, we re-estimate the model where households have a CRRA preference specification, which is often used in the business cycle literature such as Guerron-Quintana (2012). Moe specifically, the utility function is of the form:s

$$u(C_t, h_t) = \frac{\left[C_t \exp\left(-\frac{\psi}{1+\theta} h_t^{1+\theta}\right)\right]^{1-\sigma} - 1}{1-\sigma}, \tag{1.30}$$

where $\theta > 0$ is a parameter related with the labor elasticity and $\psi > 0$ is a scale parameter. Table 1.10 reports the shares of output, consumption, investment and trade balance explained by different types of common shocks for the CRRA case as well as the baseline (GHH) case. Even with a different preference specification, we find a significant contribution of common shocks for all four variables: 43% for output, 41% for consumption, 34% for investment, and 46% for trade balance. Furthermore, other results in the baseline model also hold for the CRRA case. For example, business cycles in small open economies can be attributed to multiple common shocks: common trend and stationary productivity shocks are important for output and consumption while interest premium and preference shocks are important for investment and trade balance. Therefore, when we apply the DFM estimation method to the artificial data generated from the model with CRRA preferences, we find the same result as the baseline model, namely that the DFM approach falls short at uncovering the role of common shocks when there are multiple underlying common shocks in the data generating process.

1.8 Conclusion

In this paper, we show that common shocks play a large role in driving business cycles of small open economies between 1900 and 2006 in a structural estimation using Bayesian methods. Although common shocks are more important for small developed than developing countries, the fact that 45.5% of output fluctuations in developing countries indicates a significant influence of outside shocks to developing countries. As developing countries are more volatile than small developed countries, this variance decomposition suggests that outside shocks may have larger impacts in levels to developing countries. Therefore, it would be interesting to further understand how the transmission mechanism differ across small developed and developing countries.

Additionally, our results point to the existence of multiple world common and group specific shocks hitting small open economies in our data, leading to a larger contribution of common shocks than estimated in reduced form factor analysis with one world common and one group specific shock. Our analysis suggests that it is important to formally test the number of factors when we carry out dynamic factor model estimation, and a promising future research is to augment the DFM approach in the international business cycle literature to include several types of common factors.

As we look at the whole 100 years of data, we find that common shocks are especially important when countries are more open, and the large shocks hitting the world economy such as the Great Depression have had a large impact on all countries, developed and developing alike. Therefore, we can expect that the recent recession and crisis in the U.S. and Europe may have caused output to fall significantly in not only small developed countries with strong financial links with the U.S. and Europe, but also in developing countries. Another line of research could utilize richer data set for the Great Recession to estimate an elaborative model with the propagation of shocks to small open economies. Finally, our model does not allow for transmission mechanism of idiosyncratic shocks across countries, which may contaminate the estimates of common shocks. Although we argue that this problem is small as we include several countries of small sizes, future research can purge out these effects from the estimated common shocks by modeling explicitly trade and financial linkages across countries.

1.9 Figures and Tables

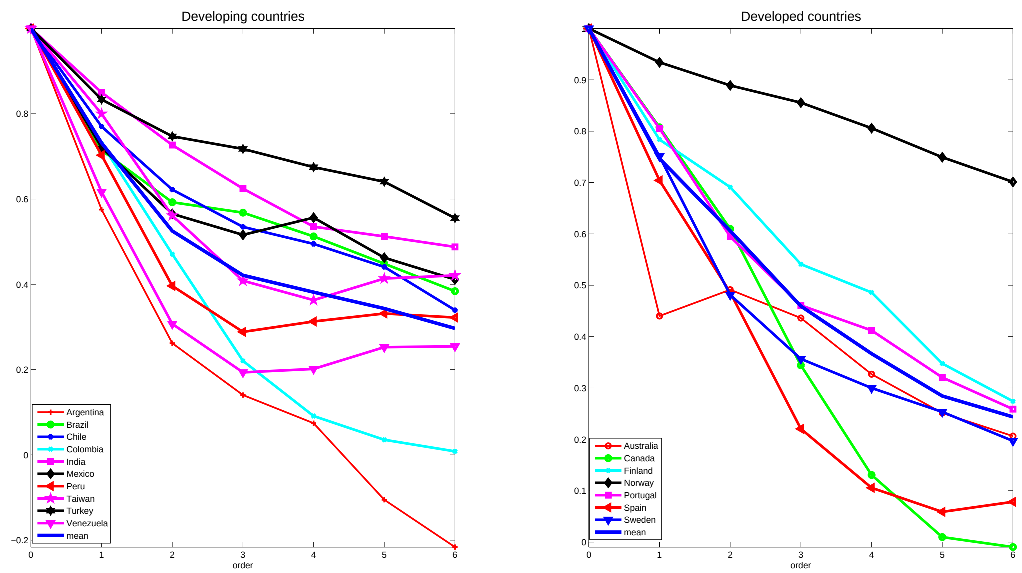

Figure 1.1: Autocorrelation functions of trade balance to output ratio for developing and small developed countries: 1900 - 2006

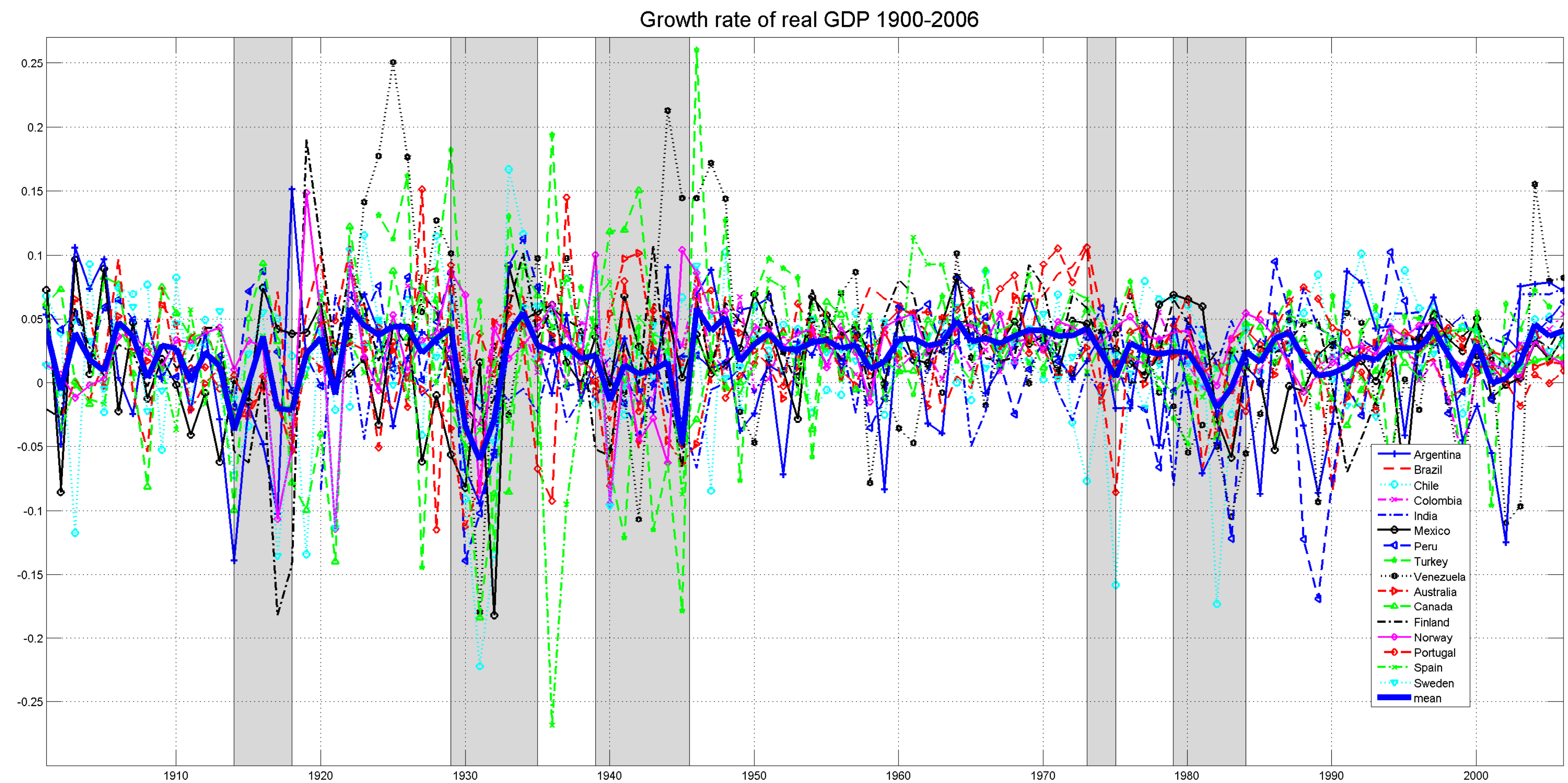

Figure 1.2: Output growth rates for 16 small open economies 1900 and 2006 excluding Taiwan. Shaded regions are major historical events.

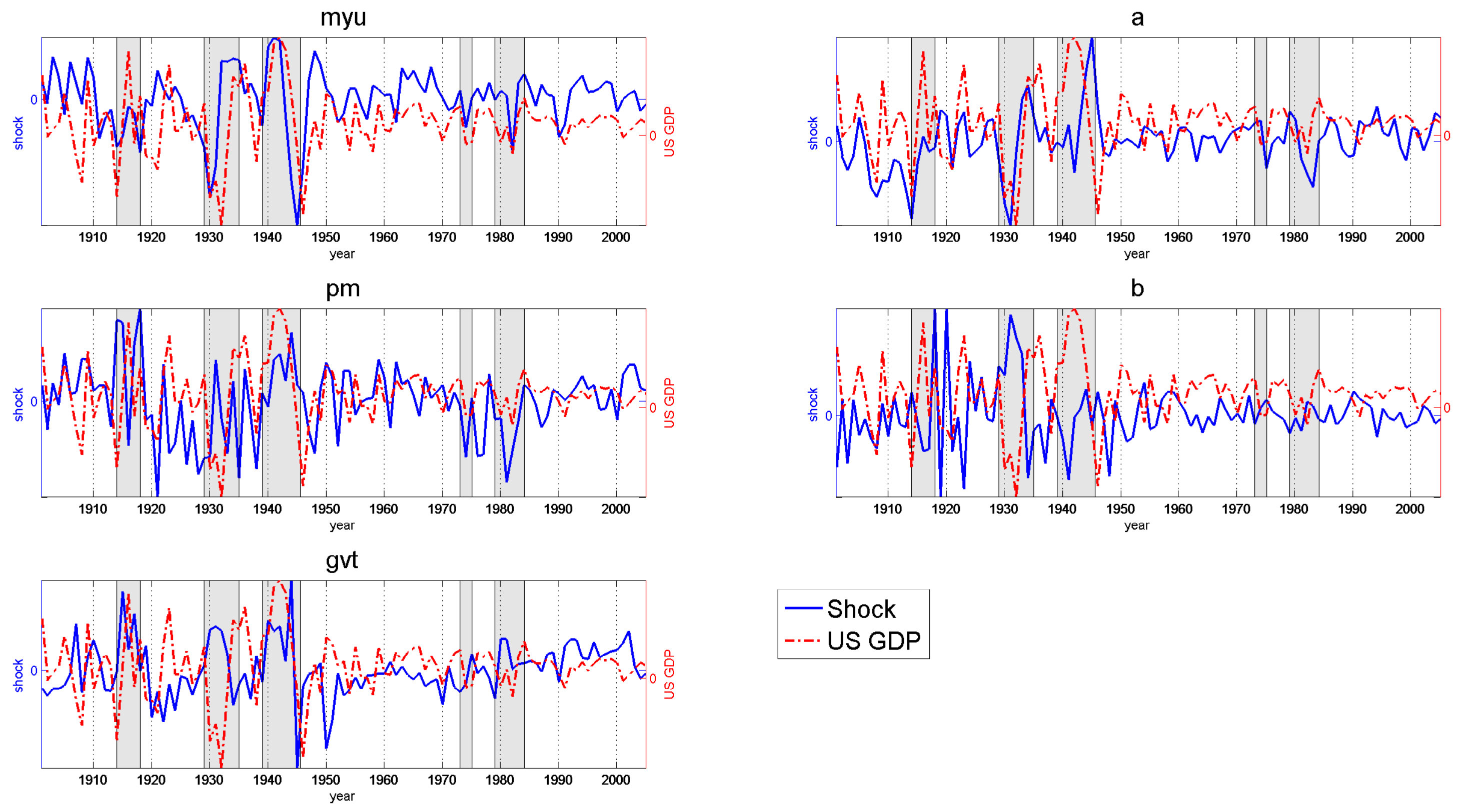

Figure 1.3: Recovered world common shocks (blue ine) against U.S. GDP growth rate (red dashed line) between 1900 and 2006. The recovered shocks were calculated using the posterior mean of the estimated parameters. Shaded regions are major historical events.

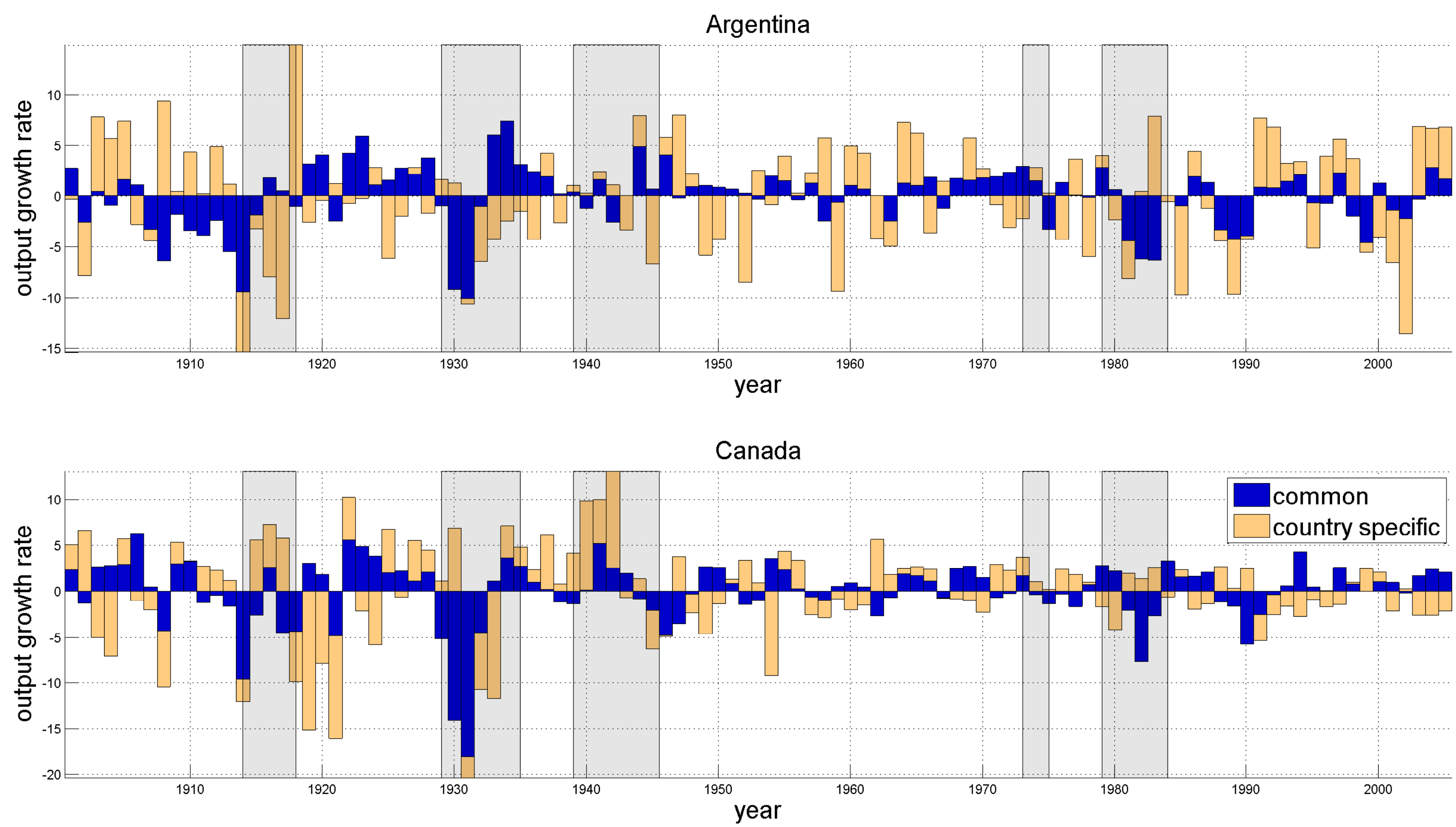

Figure 1.4: Historical decomposition of common and country specific shocks for output growth rate between 1900 and 2006 for Argentina (top panel) and Canada (bottom panel)

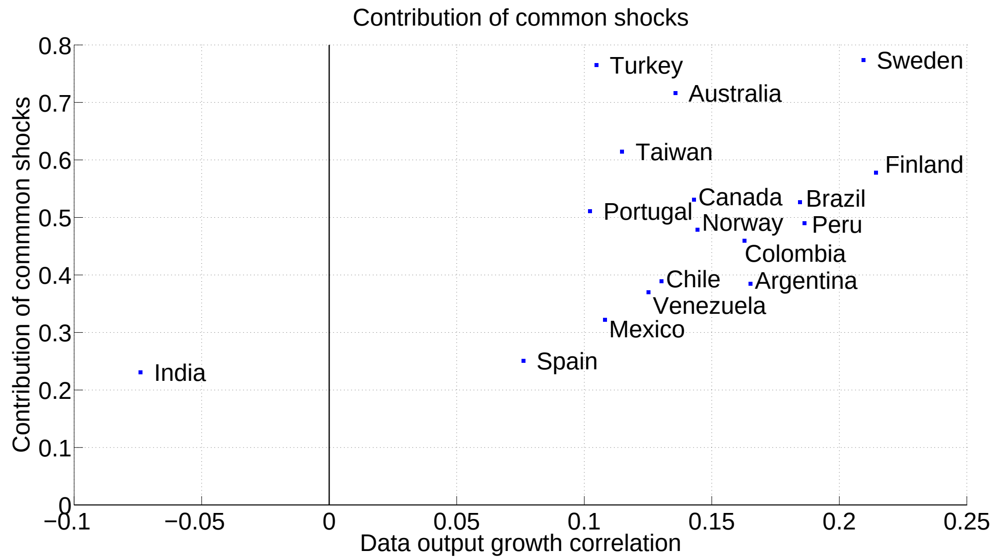

Figure 1.5: Scatter plot of the contribution of common shocks against the average correlation of each country with others in the data set

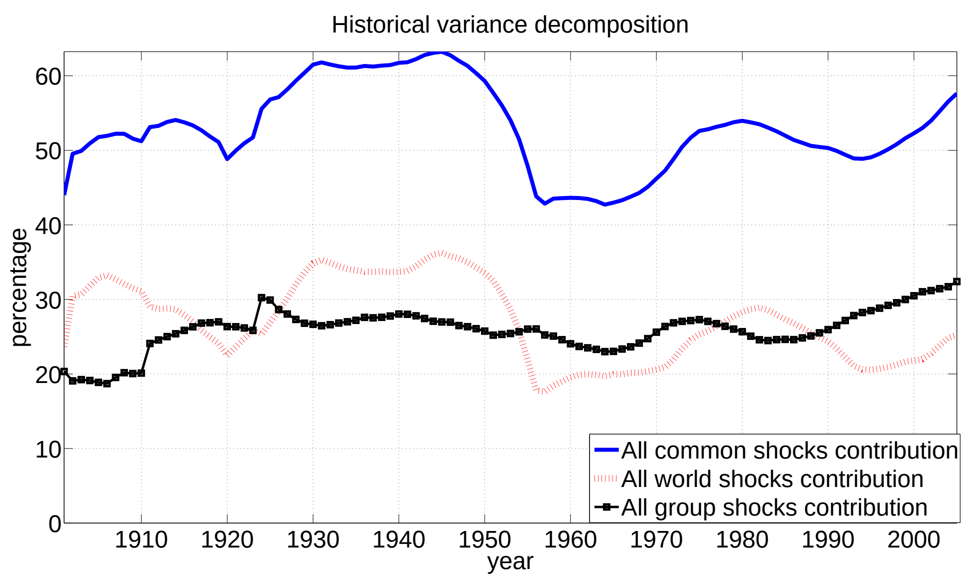

Figure 1.6: The contribution of common shocks over 20 year rolling over window (centered moving average) between 1900 and 2006. Note: before 1910 (after 1996), the contribution is calculated as rolling over of all the years before (after) each date.

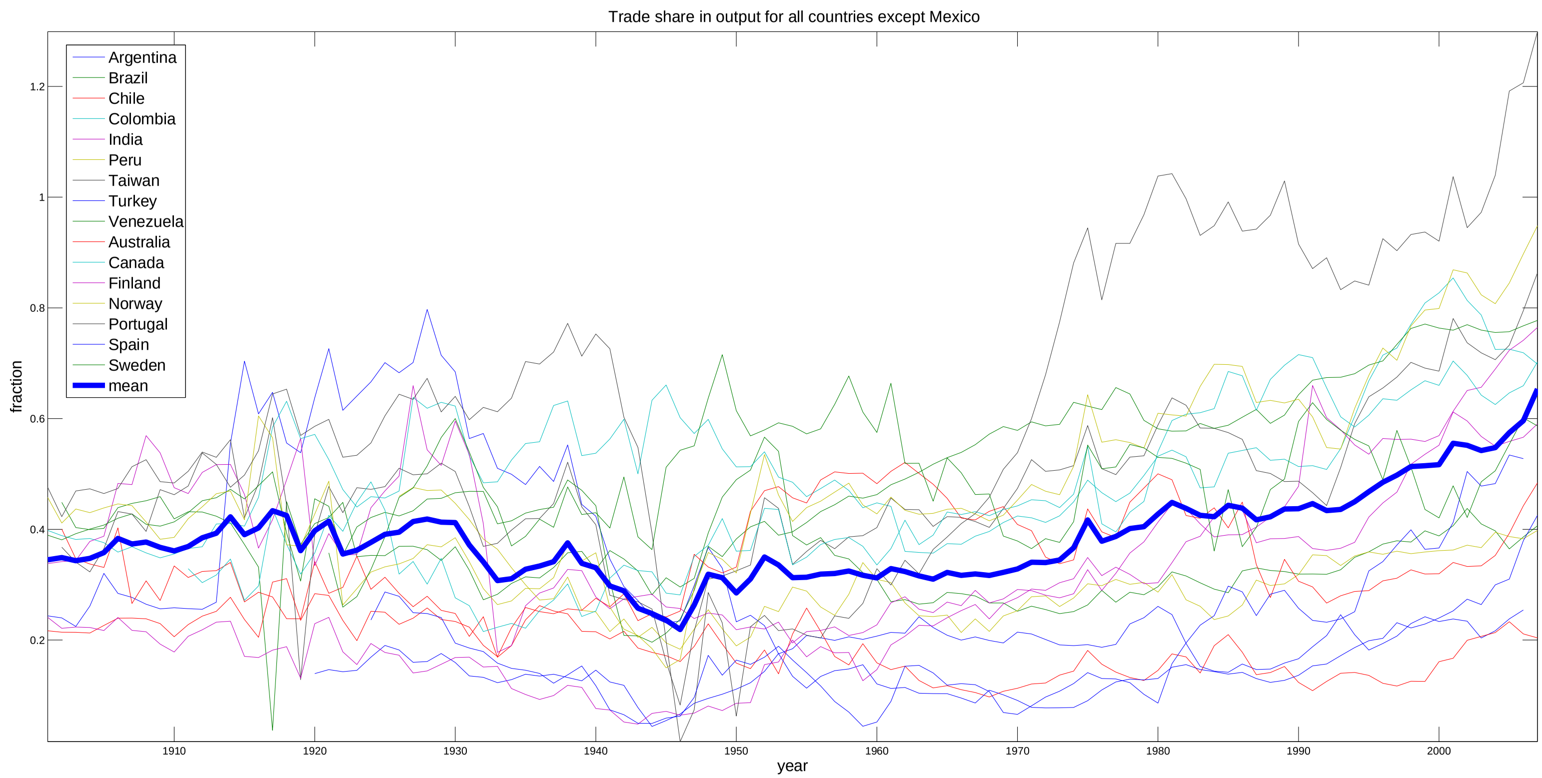

Figure 1.7: Total trade (exports and imports) as a Share of GDP over time for all excluding Mexico: 1900-2006

Table 1.1: Data availability

Country	Y	C	Inv	tby
Argentina	1900-2006	1900-2006	1900-2006	1900-2006
Brazil	1901-2006	1901-2006	1901-2006	1901-2006
Chile	1900-2006	1900-2006	1900-2006	1900-2006
Colombia	1925-2006	1925-2006	1925-2006	1925-2006
India	1919-2006	1919-2006	1919-2006	1919-2006
Mexico	1900-2006	1900-2006	1900-2006	1900-2006
Peru	1900-2006	1900-2006	1900-2006	1900-2006
Taiwan	1901-2006	1901-2006	1901-2006	1901-2006
Turkey	1923-2006	1923-2006	1923-2006	1923-2006
Venezuela	1920-2006	1920-2006	1920-2006	1920-2006
Australia	1901-2006	1901-2006	1901-2006	1901-2006
Canada	1900-2006	1900-2006	1900-2006	1900-2006
Finland	1900-2006	1900-2006	1900-2006	1900-2006
Norway	1900-2006	1900-2006	1900-2006	1900-2006
Portugal	1910-2006	1910-2006	1910-2006	1910-2006
Spain	1900-2006	1900-2006	1900-2006	1900-2006
Sweden	1900-2006	1900-2006	1900-2006	1900-2006

Table 1.2: Average Second moments: 1900-2006

(a) Within country second moments

	gy	gc	gi	tby	gy,gc	gy,gi	gy,tby	gc,tby	gi,tby	gy	gc	gi	tby
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Developing countries													
Argentina	5.37	7.56	20.29	5.12	0.74	0.67	-0.05	-0.27	-0.21	0.11	-0.01	0.32	0.58
Brazil	4.09	7.47	21.40	3.44	0.50	0.41	-0.17	-0.15	0.03	0.21	-0.26	0.18	0.70
Chile	6.29	9.32	24.10	7.79	0.64	0.55	0.18	-0.04	-0.08	0.10	0.08	0.06	0.76
Col	2.40	6.16	17.98	3.63	0.55	0.26	-0.11	-0.08	-0.22	0.28	-0.23	-0.22	0.73
India	3.38	4.27	12.12	1.56	0.55	0.23	-0.28	-0.20	-0.15	0.13	-0.16	0.08	0.83
Mexico	4.24	6.14	19.86	4.22	0.67	0.56	-0.19	-0.29	-0.07	0.00	-0.09	0.22	0.72
Peru	4.90	4.73	17.54	4.59	0.84	0.73	0.02	-0.03	-0.03	0.43	0.38	0.32	0.70
Taiwan	9.01	9.18	22.03	5.65	0.85	0.21	0.04	-0.05	-0.06	0.35	0.28	-0.04	0.78
Turkey	7.38	6.42	14.06	3.61	0.65	0.45	-0.11	-0.17	-0.14	-0.18	0.09	0.21	0.83
Ven	7.67	10.07	20.35	7.27	0.67	0.84	-0.07	-0.08	-0.20	0.49	-0.04	0.38	0.63
mean	**5.47**	**7.13**	**18.97**	**4.69**	**0.67**	**0.49**	**-0.07**	**-0.14**	**-0.11**	**0.19**	**0.00**	**0.15**	**0.73**
Small Developed Countries													
Australia	3.25	5.09	13.48	3.79	0.28	0.41	0.04	-0.09	-0.16	0.50	0.15	0.34	0.45
Canada	5.15	4.63	13.09	3.96	0.71	0.50	0.13	0.16	-0.02	0.36	0.02	0.46	0.81
Finland	4.72	6.04	14.42	5.87	0.79	0.50	0.21	0.14	0.15	0.27	0.16	0.18	0.79
Norway	3.83	4.73	15.04	8.33	0.85	0.69	-0.02	0.00	-0.15	-0.03	-0.05	-0.16	0.94
Portugal	4.67	4.42	13.44	5.07	0.82	0.32	0.06	-0.08	-0.15	-0.05	0.19	0.14	0.81
Spain	4.55	8.30	11.85	2.35	0.85	0.46	-0.17	-0.20	-0.09	0.28	-0.06	0.36	0.71
Sweden	3.50	4.42	10.45	3.21	0.67	0.68	-0.06	-0.21	-0.04	-0.02	-0.09	0.17	0.76
mean	**4.24**	**5.38**	**13.11**	**4.65**	**0.71**	**0.51**	**0.03**	**-0.04**	**-0.07**	**0.19**	**0.05**	**0.21**	**0.75**

(b) Cross country correlation

xi,xj	gy			gc			gi			tby		
	ALL	EM	DEV	ALL	EM	DEV	ALL	EM	DEV	ALL	EM	DEV
mean	0.13	0.14	0.22	0.07	0.06	0.15	0.18	0.21	0.18	0.11	0.23	0.04

Table 1.2: (c): Cross-country correlation of output growth rate between 1900 and 2006

	Arg	**Aus**	**Bra**	**Can**	**Chile**	**Col**	**Fin**	**Ind**	**Mex**	**Nor**	**Peru**	**Port**	**Spain**	**Swe**	**Taiw**	**Turk**	**Vene**
Arg	1.00	0.15	0.24	0.21	0.27	0.25	0.15	-0.08	0.25	0.14	0.39	0.17	0.12	0.16	0.13	0.11	0.43
Aus	0.15	1.00	0.12	0.53	0.27	-0.01	0.31	0.17	0.25	-0.12	0.15	0.05	0.10	-0.09	0.30	-0.11	-0.21
Bra	0.24	0.12	1.00	0.15	0.20	0.51	0.53	-0.22	0.18	0.27	0.44	0.15	-0.04	0.28	0.08	0.09	0.27
Can	0.21	0.53	0.15	1.00	0.29	0.06	0.22	0.02	0.24	-0.03	0.21	0.00	0.21	0.07	0.09	-0.09	0.10
Chile	0.27	0.27	0.20	0.29	1.00	0.23	0.17	0.03	0.26	0.20	0.32	0.01	-0.03	0.04	-0.01	0.25	0.18
Col	0.25	-0.01	0.51	0.06	0.23	1.00	0.21	-0.18	-0.01	0.26	0.36	0.06	0.01	0.22	0.00	0.15	0.47
Fin	0.15	0.31	0.53	0.22	0.17	0.21	1.00	-0.01	0.28	0.13	0.27	0.30	0.10	0.49	0.30	0.10	0.06
Ind	-0.08	0.17	-0.22	0.02	0.03	-0.18	-0.01	1.00	-0.09	-0.08	-0.09	-0.12	0.10	-0.06	0.17	-0.03	-0.22
Mex	0.25	0.25	0.18	0.24	0.26	-0.01	0.28	-0.09	1.00	-0.05	0.28	0.05	-0.01	0.28	0.06	0.17	0.05
Nor	0.14	-0.12	0.27	-0.03	0.20	0.26	0.13	-0.08	-0.05	1.00	0.21	0.07	-0.13	0.48	0.04	0.18	0.33
Peru	0.39	0.15	0.44	0.21	0.32	0.36	0.27	-0.09	0.28	0.21	1.00	-0.03	0.07	0.30	0.00	0.20	0.32
Port	0.17	0.05	0.15	0.00	0.01	0.06	0.30	-0.12	0.05	0.07	-0.03	1.00	0.35	0.20	0.21	-0.10	0.06
Spain	0.12	0.10	-0.04	0.21	-0.03	0.01	0.10	0.10	-0.01	-0.13	0.07	0.35	1.00	0.01	0.24	-0.13	-0.07
Swe	0.16	-0.09	0.28	0.07	0.04	0.22	0.49	-0.06	0.28	0.48	0.30	0.20	0.01	1.00	0.12	0.33	0.28
Taiw	0.13	0.30	0.08	0.09	-0.01	0.00	0.30	0.17	0.06	0.04	0.00	0.21	0.24	0.12	1.00	0.42	-0.14
Turk	0.11	-0.11	0.09	-0.09	0.25	0.15	0.10	-0.03	0.17	0.18	0.20	-0.10	-0.13	0.33	0.42	1.00	0.13
Vene	0.42	-0.20	0.29	0.07	0.22	0.45	0.12	-0.20	0.16	0.28	0.36	0.15	-0.11	0.35	-0.20	0.14	1.00

Table 1.3: Calibrated Parameters

Parameter	Description	Value
σ	Risk aversion	2
α	Capital share	0.32
θ	Labor elasticity	1.6
β	Discount rate	0.9224

Table 1.4: Common shocks Parameter Estimates

Para	Prior	Posterior	Para	Prior	Posterior	Para	Prior	Posterior
$\rho_{\mu c}$	B	0.68	$\rho_{\mu g1}$	B	0.57	$\rho_{\mu g2}$	B	0.63
	(0.5,0.2)	(0.58,0.77)		(0.5,0.2)	(0.35,0.76)		(0.5,0.2)	(0.48,0.76)
ρ_{ac}	B	0.84	ρ_{ag1}	B	0.83	ρ_{ag2}	B	0.78
	(0.5,0.2)	(0.76,0.91)		(0.5,0.2)	(0.74,0.91)		(0.5,0.2)	(0.69,0.86)
ρ_{pmc}	B	0.91	ρ_{pmg1}	B	0.97	ρ_{pmg2}	B	0.99
	(0.5,0.2)	(0.83,0.97)		(0.5,0.2)	(0.92,0.99)		(0.5,0.2)	(0.98,1.00)
ρ_{bc}	B	0.98	ρ_{bg1}	B	0.90	ρ_{bg1}	B	0.94
	(0.5,0.2)	(0.98,0.99)		(0.5,0.2)	(0.83,0.95)		(0.5,0.2)	(0.89,0.97)
ρ_{gc}	B	0.68	ρ_{gg1}	B	0.59	ρ_{gg2}	B	0.94
	(0.5,0.2)	(0.57,0.77)		(0.5,0.2)	(0.45,0.74)		(0.5,0.2)	(0.89,0.98)

Notes: All results are reported using 4 chains of 200,000 draws from the posterior distribution. g1 denotes developing group-specific shock and g2 denotes developed group-specific shocks. The numbers in parentheses for the posterior are the 5% and 95% confidence interval of the posterior distribution.

Table 1.5: (a): Posterior Estimates for Developing Countries

Par	Prior	Arg	Brazil	Chile	Col	India	Mexico	Peru	Taiwan	Turkey	Ven
s	G	0.83	0.15	0.61	0.17	0.35	0.27	0.18	0.20	0.34	0.18
	(0.5,0.5)	(0.62,1.07)	(0.09,0.25)	(0.46,0.78)	(0.08,0.28)	(0.19,0.53)	(0.14,0.43)	(0.12,0.25)	(0.12,0.31)	(0.21,0.48)	(0.10,0.29)
ϕ	G	2.64	1.17	2.92	2.08	5.04	1.09	0.31	0.65	5.37	0.09
	(5,3)	(1.65,3.69)	(0.82,1.56)	(2.32,3.59)	(1.22,3.11)	(2.81,7.43)	(0.54,1.83)	(0.18,0.48)	(0.37,0.98)	(3.20,7.86)	(0.04,0.16)
ucost	B	0.88	0.46	0.74	0.26	0.70	0.86	0.76	0.33	0.39	0.65
	(0.5,0.15)	(0.80,0.95)	(0.31,0.61)	(0.57,0.89)	(0.14,0.41)	(0.51,0.88)	(0.74,0.96)	(0.58,0.90)	(0.19,0.47)	(0.22,0.60)	(0.47,0.83)
$\rho_{\mu j}$	B	0.52	0.74	0.46	0.59	0.69	0.50	0.68	0.77	0.38	0.58
	(0.5,0.2)	(0.22,0.80)	(0.59,0.87)	(0.20,0.74)	(0.30,0.82)	(0.54,0.82)	(0.18,0.78)	(0.55,0.82)	(0.64,0.88)	(0.12,0.69)	(0.40,0.75)
ρ_{aj}	B	0.75	0.56	0.66	0.72	0.48	0.86	0.73	0.47	0.55	0.76
	(0.5,0.2)	(0.57,0.88)	(0.22,0.85)	(0.48,0.81)	(0.43,0.91)	(0.17,0.81)	(0.77,0.94)	(0.47,0.90)	(0.15,0.82)	(0.24,0.83)	(0.53,0.90)
ρ_{pmj}	B	0.94	0.99	0.95	0.95	0.97	0.87	0.90	0.95	0.97	0.95
	(0.5,0.2)	(0.88,0.98)	(0.97,1.00)	(0.91,0.98)	(0.90,0.98)	(0.95,0.99)	(0.64,0.98)	(0.75,0.97)	(0.90,0.99)	(0.95,0.99)	(0.89,0.98)
ρ_{bj}	B	0.74	0.61	0.73	0.72	0.82	0.68	0.84	0.70	0.68	0.82
	(0.5,0.2)	(0.63,0.83)	(0.44,0.76)	(0.63,0.81)	(0.56,0.85)	(0.71,0.91)	(0.51,0.81)	(0.76,0.90)	(0.59,0.80)	(0.51,0.81)	(0.68,0.92)
ρ_{gj}	B	0.83	0.85	0.80	0.85	0.87	0.86	0.79	0.91	0.87	0.82
	(0.5,0.2)	(0.66,0.95)	(0.77,0.91)	(0.69,0.87)	(0.77,0.91)	(0.77,0.93)	(0.78,0.93)	(0.73,0.85)	(0.86,0.96)	(0.80,0.92)	(0.73,0.89)
$\sigma_{\mu j}$	U	1.33	1.52	1.37	0.46	2.01	0.87	2.46	2.78	0.42	2.80
	(10,5.7)	(0.30,2.47)	(1.04,2.00)	(0.32,2.49)	(0.06,0.92)	(1.53,2.45)	(0.13,1.79)	(1.46,3.30)	(1.75,3.78)	(0.04,1.04)	(0.99,4.24)
σ_{aj}	U	2.46	0.67	2.44	0.48	0.27	2.28	1.00	0.43	1.13	2.11
	(10,5.7)	(2.04,2.89)	(0.16,1.15)	(1.93,2.95)	(0.11,0.78)	(0.03,0.69)	(1.93,2.67)	(0.17,1.80)	(0.05,0.97)	(0.28,1.93)	(0.87,3.15)
σ_{pmj}	U	16.68	2.71	32.18	7.85	7.84	4.48	1.81	4.00	20.44	1.61
	(100,57.7)	(12.01,21.74)	(1.91,3.61)	(25.80,38.80)	(4.81,11.39)	(4.44,11.55)	(2.33,7.34)	(1.18,2.53)	(2.46,5.60)	(12.03,30.91)	(1.07,2.30)
σ_{bj}	U	7.99	6.46	7.89	7.32	4.13	6.53	5.07	7.25	4.16	11.66
	(100,57.7)	(6.76,9.57)	(5.15,7.91)	(6.83,9.22)	(5.71,9.71)	(3.17,5.50)	(5.21,7.99)	(4.15,6.39)	(6.12,8.61)	(3.29,5.11)	(7.43,17.33)
σ_{gj}	U	1.08	3.83	4.52	2.84	2.74	2.75	2.82	2.41	4.49	5.88
	(100,57.7)	(0.86,1.30)	(3.43,4.28)	(4.02,5.02)	(2.41,3.29)	(2.37,3.13)	(2.26,3.19)	(2.50,3.18)	(1.75,3.15)	(3.86,5.15)	(5.21,6.61)
$v_{\mu c}$	U	0.82	0.52	1.21	-0.05	0.45	0.79	1.07	2.16	-0.53	-0.46
	(0,28.9)	(0.15,1.55)	(0.07,0.98)	(0.42,2.06)	(-0.31,0.22)	(-0.03,0.91)	(0.17,1.42)	(0.35,1.81)	(1.20,3.24)	(-1.14,0.06)	(-1.29,0.39)
v_{ac}	U	1.93	1.17	1.78	0.45	-0.40	1.10	1.73	-1.03	-0.42	1.80
	(0,28.9)	(1.34,2.51)	(0.78,1.60)	(1.14,2.49)	(0.25,0.67)	(-0.74,-0.08)	(0.61,1.61)	(1.15,2.33)	(-1.76,-0.34)	(-1.11,0.29)	(1.04,2.61)
v_{pmc}	U	6.15	1.06	8.07	2.05	1.74	-0.53	0.68	0.02	8.42	0.45
	(0,28.9)	(2.35,10.64)	(0.40,1.75)	(3.67,12.67)	(0.18,4.00)	(-0.11,4.01)	(-1.75,0.52)	(0.28,1.13)	(-1.02,1.11)	(2.46,15.53)	(0.05,0.85)
v_{bc}	U	1.89	12.71	10.26	-5.30	9.57	4.53	12.42	-1.95	-4.13	-11.24
	(0,28.9)	(0.22,4.37)	(4.81,20.53)	(3.18,17.34)	(-13.89,3.14)	(5.06,14.51)	(-1.68,11.02)	(7.26,17.48)	(-7.17,2.93)	(-9.66,1.36)	(-27.59,3.18)

Table 1.5: (a): Posterior Estimates for Developing Countries (continued)

Par	Prior	Arg	Brazil	Chile	Col	India	Mexico	Peru	Taiwan	Turkey	Ven
v_{gc}	U	0.84	0.45	0.06	1.51	0.50	0.82	0.97	-0.98	1.93	0.62
	(0,28.9)	(0.52,1.16)	(-0.30,1.19)	(-0.93,1.14)	(0.74,2.28)	(-0.17,1.14)	(0.16,1.45)	(0.35,1.61)	(-1.72,-0.27)	(0.92,2.97)	(-0.46,1.71)
$v_{\mu g}$	U	0.96	0.50	-0.54	0.29	-0.41	0.32	0.24	1.06	0.19	0.93
	(0,28.9)	(0.15,2.05)	(-0.98,1.52)	(-1.80,0.79)	(-0.61,0.80)	(-1.09,0.34)	(-0.57,1.17)	(-0.70,1.19)	(-0.74,2.66)	(-0.54,0.89)	(-0.68,2.84)
v_{ag}	U	0.46	0.31	0.97	0.15	-0.11	0.66	0.67	1.62	2.45	0.95
	(0,28.9)	(0.06,1.03)	(-0.04,0.71)	(0.30,1.64)	(-0.03,0.38)	(-0.44,0.22)	(0.12,1.21)	(0.19,1.12)	(1.04,2.23)	(1.68,3.17)	(0.26,1.69)
v_{pmg}	U	3.87	1.36	4.97	2.01	1.48	2.88	1.07	2.50	3.34	0.32
	(0,28.9)	(0.62,8.23)	(0.67,2.08)	(-0.84,10.88)	(0.05,4.43)	(-0.39,3.51)	(1.42,4.72)	(0.58,1.61)	(1.35,3.73)	(-1.75,9.19)	(-0.08,0.76)
v_{bg}	U	1.90	9.80	1.02	-7.36	3.34	7.90	2.54	-1.11	3.03	12.31
	(0,28.9)	(0.27,4.10)	(6.20,14.11)	(-1.68,3.78)	(-11.01,-3.88)	(1.19,5.78)	(4.86,11.70)	(0.96,4.40)	(-3.46,1.38)	(0.40,5.95)	(6.66,19.15)
v_{gg}	U	0.28	0.24	0.74	-0.76	0.92	1.42	0.10	2.45	0.81	-0.27
	(0,28.9)	(0.05,0.54)	(-0.52,0.99)	(-0.01,1.55)	(-1.46,-0.06)	(0.35,1.47)	(0.70,2.27)	(-0.55,0.79)	(1.57,3.18)	(-0.28,1.97)	(-1.37,0.84)

Table 1.5: (b): Posterior Estimates for Small Developed Countries

Par	Prior	Australia	Canada	Finland	Norway	Portugal	Spain	Sweden
s	G	1.00	0.57	0.48	0.07	0.11	0.79	0.13
	(0.5,0.5)	(0.69,1.35)	(0.39,0.77)	(0.26,0.69)	(0.05,0.09)	(0.06,0.17)	(0.49,1.12)	(0.05,0.35)
ϕ	G	1.49	0.65	1.19	0.19	0.08	3.07	0.18
	(5,3)	(0.89,2.22)	(0.40,0.95)	(0.40,2.01)	(0.13,0.26)	(0.05,0.12)	(1.66,4.91)	(0.07,0.47)
ucost	B	0.11	0.71	0.44	0.90	0.41	0.92	0.55
	(0.5,0.15)	(0.04,0.19)	(0.55,0.86)	(0.25,0.65)	(0.81,0.97)	(0.26,0.58)	(0.85,0.98)	(0.41,0.70)
$\rho_{\mu j}$	B	0.61	0.62	0.60	0.69	0.44	0.45	0.51
	(0.5,0.2)	(0.29,0.82)	(0.41,0.76)	(0.32,0.82)	(0.39,0.91)	(0.16,0.71)	(0.17,0.74)	(0.25,0.75)
ρ_{aj}	B	0.60	0.65	0.72	0.73	0.56	0.89	0.57
	(0.5,0.2)	(0.26,0.87)	(0.36,0.83)	(0.59,0.85)	(0.60,0.85)	(0.24,0.86)	(0.79,0.96)	(0.25,0.87)
ρ_{pmj}	B	0.77	0.92	0.90	0.44	0.56	0.92	0.95
	(0.5,0.2)	(0.54,0.95)	(0.86,0.97)	(0.80,0.96)	(0.12,0.81)	(0.21,0.88)	(0.86,0.97)	(0.88,0.99)
ρ_{bj}	B	0.86	0.53	0.75	0.86	0.96	0.65	0.74
	(0.5,0.2)	(0.80,0.91)	(0.19,0.86)	(0.50,0.89)	(0.63,0.96)	(0.93,0.98)	(0.46,0.79)	(0.56,0.87)
ρ_{gj}	B	0.66	0.66	0.52	0.48	0.84	0.90	0.94
	(0.5,0.2)	(0.55,0.75)	(0.55,0.74)	(0.35,0.66)	(0.22,0.73)	(0.80,0.88)	(0.77,0.97)	(0.91,0.97)
$\sigma_{\mu j}$	U	0.57	2.47	0.63	1.05	1.20	0.54	0.84
	(10,5.7)	(0.10,1.02)	(0.74,3.58)	(0.07,1.40)	(0.44,1.70)	(0.16,2.20)	(0.06,1.20)	(0.32,1.34)
σ_{aj}	U	0.24	1.20	1.17	1.82	0.74	2.21	0.29
	(10,5.7)	(0.03,0.55)	(0.18,2.16)	(0.69,1.56)	(1.48,2.19)	(0.15,1.31)	(1.94,2.49)	(0.03,0.74)
σ_{pmj}	U	9.81	4.19	8.70	0.64	1.02	8.18	0.96
	(100,57.7)	(7.50,12.14)	(2.99,5.57)	(3.71,14.10)	(0.12,1.13)	(0.55,1.59)	(4.47,13.14)	(0.41,2.46)
σ_{bj}	U	9.26	0.79	3.78	4.17	10.68	5.51	4.37
	(100,57.7)	(7.52,11.54)	(0.09,1.94)	(2.46,5.36)	(0.70,7.58)	(6.53,17.22)	(4.32,6.71)	(3.24,5.86)
σ_{gj}	U	4.21	2.86	3.22	1.15	3.04	2.60	1.36
	(100,57.7)	(3.75,4.73)	(2.53,3.24)	(2.62,3.78)	(0.83,1.47)	(2.70,3.42)	(2.28,2.99)	(1.20,1.53)
$v_{\mu c}$	U	1.32	2.11	0.88	0.02	0.24	1.07	0.15
	(0,28.9)	(0.98,1.66)	(1.30,2.98)	(0.39,1.44)	(-0.61,0.62)	(-0.23,0.74)	(0.46,1.71)	(-0.25,0.59)
v_{ac}	U	0.11	1.58	0.71	0.92	0.28	0.36	0.21
	(0,28.9)	(-0.14,0.35)	(1.05,2.16)	(0.31,1.15)	(0.48,1.43)	(-0.06,0.62)	(-0.10,0.80)	(-0.11,0.55)
v_{pmc}	U	4.26	0.14	0.88	0.33	0.87	4.91	-0.01
	(0,28.9)	(2.78,5.81)	(-0.64,1.00)	(-1.01,3.14)	(-0.09,0.73)	(0.55,1.28)	(2.18,8.47)	(-0.25,0.31)
v_{bc}	U	1.38	30.31	-12.89	3.95	3.01	5.07	2.93
	(0,28.9)	(-4.36,7.05)	(21.29,40.53)	(-18.48,-7.64)	(-0.57,8.62)	(-0.08,6.37)	(1.39,8.78)	(-2.25,7.55)
v_{gc}	U	0.89	1.39	2.89	0.02	0.62	-0.10	0.16
	(0,28.9)	(0.15,1.63)	(0.74,2.01)	(2.14,3.66)	(-0.35,0.42)	(-0.01,1.27)	(-0.62,0.42)	(-0.15,0.48)
$v_{\mu g}$	U	0.11	-0.40	1.16	0.94	1.76	1.10	0.74
	(0,28.9)	(0.01,0.30)	(-1.28,0.36)	(0.58,1.81)	(0.28,1.57)	(1.02,2.49)	(0.38,1.78)	(0.28,1.19)
v_{ag}	U	0.11	0.63	0.90	1.23	-0.21	-0.40	1.28
	(0,28.9)	(0.01,0.26)	(0.17,1.12)	(0.51,1.31)	(0.74,1.70)	(-0.59,0.18)	(-0.84,0.02)	(1.00,1.56)
v_{pmg}	U	2.25	-0.34	-3.70	-1.47	0.06	3.43	-0.30
	(0,28.9)	(0.66,4.20)	(-0.93,0.18)	(-6.51,-1.35)	(-1.85,-1.12)	(-0.14,0.29)	(1.53,6.00)	(-0.75,-0.08)
v_{bg}	U	1.64	-0.46	-1.23	-5.53	1.13	-3.25	-3.27
	(0,28.9)	(0.18,3.76)	(-4.35,4.16)	(-3.78,1.29)	(-9.82,-2.05)	(-1.30,3.51)	(-5.52,-1.12)	(-6.53,-0.20)
v_{gg}	U	0.90	0.79	2.11	1.38	-0.16	-0.47	0.32
	(0,28.9)	(0.39,1.46)	(0.40,1.23)	(1.54,2.80)	(1.07,1.71)	(-0.67,0.36)	(-1.02,0.08)	(0.03,0.63)

Notes: All results are reported using 4 chains of 200,000 draws from the posterior distribution. g1 denotes developing group-specific shock and g2 denotes developed group-specific shocks. The numbers in parentheses for the posterior are the 5% and 95% confidence interval of the posterior distribution

Table 1.6: Average second moments: Data and Model: 1900-2006

		gy			gc			gi			tby		
		ALL	EM	DEV	ALL	EM	DEV	ALL	EM	DEV	ALL	EM	DEV
σ_x													
	Data	6.01	6.62	5.15	7.85	8.76	6.55	17.13	19.27	14.06	5.92	6.57	4.92
	Model	6.55	7.26	5.53	6.79	7.60	5.64	17.10	19.90	13.08	5.16	5.72	4.35
		(5.80,6.27)	(6.33,6.93)	(4.90,5.45)	(7.63,8.09)	(8.45,9.07)	(6.30,6.83)	(16.65,17.57)	(18.61,19.90)	(13.55,14.62)	(5.42,6.68)	(5.80,7.83)	(4.48,5.69)
$\rho_{x,gy}$													
	Data	1.00	1.00	1.00	0.68	0.67	0.71	0.50	0.49	0.51	-0.03	-0.07	0.03
	Model	1.00	1.00	1.00	0.73	0.72	0.75	0.34	0.32	0.35	-0.03	-0.04	-0.02
		(1.00,1.00)	(1.00,1.00)	(1.00,1.00)	(0.72,0.75)	(0.70,0.74)	(0.73,0.77)	(0.32,0.36)	(0.30,0.35)	(0.32,0.39)	(-0.04,-0.02)	(-0.06,-0.02)	(-0.04,0.00)
$\rho_{x,tby}$													
	Data	-0.03	-0.07	0.03	-0.10	-0.14	-0.04	-0.09	-0.11	-0.07	1.00	1.00	1.00
	Model	-0.03	-0.04	-0.02	-0.10	-0.13	-0.06	-0.15	-0.14	-0.16	1.00	1.00	1.00
		(-0.04,-0.02)	(-0.06,-0.02)	(-0.04,0.00)	(-0.12,-0.09)	(-0.15,-0.11)	(-0.08,-0.04)	(-0.17,-0.12)	(-0.16,-0.11)	(-0.20,-0.13)	(1.00,1.00)	(1.00,1.00)	(1.00,1.00)
ρ_x													
	Data	0.19	0.19	0.19	0.02	0.00	0.05	0.17	0.15	0.21	0.74	0.73	0.75
	Model	0.08	0.09	0.07	0.02	0.01	0.03	0.22	0.20	0.25	0.67	0.64	0.71
		(0.06,0.11)	(0.06,0.13)	(0.03,0.12)	(0.00,0.03)	(-0.01,0.02)	(0.01,0.06)	(0.20,0.24)	(0.18,0.22)	(0.22,0.28)	(0.65,0.70)	(0.61,0.67)	(0.68,0.76)
ρ_{x_i,x_j}													
	Data	0.13	0.14	0.22	0.07	0.06	0.15	0.18	0.21	0.18	0.11	0.23	0.04
	Model	0.13	0.15	0.22	0.08	0.09	0.14	0.07	0.10	0.08	0.06	0.08	0.06
		(0.10,0.17)	(0.10,0.19)	(0.16,0.29)	(0.06,0.11)	(0.06,0.12)	(0.10,0.19)	(0.06,0.08)	(0.07,0.12)	(0.05,0.10)	(0.04,0.08)	(0.05,0.12)	(0.02,0.11)

Notes: The model moments are shown at the posterior median calculating from 120,000 draws from the posterior distribution. ρ_{x_i,x_j} is the correlation of the variable x between country i and country j. The numbers in parentheses for the posterior are the 5% and 95% confidence interval of the posterior distribution

Table 1.7: Average across countries contribution of common shocks to all countries between 1900 and 2006

		All	EM	DEV	All	EM	DEV	All	EM	DEV	All	EM	DEV
			gy			gc			gi			tby	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
W	μ	9.3	5.1	15.2	4.3	3.0	6.0	1.3	1.0	1.6	0.5	0.5	0.4
	a	14.2	18.6	8.0	8.2	9.4	6.4	3.1	3.6	2.3	0.5	0.6	0.4
	pm	0.3	0.2	0.4	0.3	0.2	0.3	5.3	2.8	8.9	7.6	4.4	12.1
	b	1.0	0.8	1.2	2.7	1.8	4.0	2.5	1.8	3.5	9.1	8.4	10.1
	gvt	0.2	0.2	0.3	1.0	0.7	1.4	2.2	1.9	2.5	0.7	0.6	0.9
	Total	25.0	24.9	25.1	16.4	15.1	18.2	14.3	11.2	18.8	18.3	14.4	23.9
G	μ	7.9	5.1	12.1	3.9	2.2	6.5	1.5	1.0	2.3	0.5	0.3	0.8
	a	14.0	12.7	15.8	8.5	7.6	9.6	3.3	2.4	4.6	0.8	0.8	0.7
	pm	0.7	0.3	1.2	0.4	0.2	0.6	6.2	4.9	8.1	13.9	9.9	19.7
	b	1.6	2.4	0.5	6.1	8.5	2.7	5.1	7.7	1.5	5.8	7.2	3.7
	gvt	0.1	0.1	0.1	2.0	0.5	4.1	1.4	2.0	0.5	0.6	0.8	0.4
	Total	24.4	20.6	29.7	20.9	19.1	23.5	17.6	18.0	17.0	21.6	19.0	25.3
W+G		**49.4**	**45.5**	**54.8**	**37.3**	**34.2**	**41.7**	**31.9**	**29.2**	**35.8**	**39.9**	**33.3**	**49.2**

Notes: All results are reported using the mean of variance decomposition computed from 4 chains of 200,000 draws from the posterior distribution. We take average of the mean variance decomposition across all countries (ALL), developed countries (DEV) and developing countries (EM).

Table 1.8: DSGE and Dynamic Factor Model comparison: Median contribution of World + Group common shocks

	Actual data	Artificial data	
		1 shock	
	DFM	DSGE	DFM
gy	15.5	34.1	26
gc	13.8	20	14.9
gi	16.1	8	7
tby	12.4	2.6	4

Table 1.9: Robustness check: subsamples 1900-1959 and 1960-2006

(a)

		gy			gc		
		1900-2006	1900-1960	1961-2006	1900-2006	1900-1960	1961-2006
W	μ	9.3	13.0	11.7	4.3	7.5	7.7
	a	14.2	12.0	13.9	8.2	6.8	9.5
	pm	0.3	0.2	1.1	0.3	0.6	0.6
	b	1.0	1.2	0.2	2.7	2.8	0.9
	gvt	0.2	0.3	0.2	1.0	4.1	0.5
	Total	25.0	26.7	27.1	16.4	21.8	19.1
G	μ	7.9	10.0	8.1	3.9	6.2	5.8
	a	14.0	13.8	14.9	8.5	7.9	11.0
	pm	0.7	0.4	1.2	0.4	0.6	0.7
	b	1.6	1.7	1.0	6.1	5.3	4.0
	gvt	0.1	0.4	0.2	2.0	3.1	3.3
	Total	24.4	26.4	25.3	20.9	23.1	24.9
W+G		**49.4**	**53.1**	**52.4**	**37.3**	**44.9**	**44.0**

(b) continued

		gi			tby		
		1900-2006	1900-1960	1961-2006	1900-2006	1900-1960	1961-2006
W	μ	1.3	2.7	2.6	0.5	1.6	0.6
	a	3.1	2.1	3.6	0.5	0.9	0.7
	pm	5.3	5.0	8.6	7.6	8.9	8.8
	b	2.5	3.7	0.6	9.1	12.0	14.6
	gvt	2.2	3.3	2.0	0.7	1.0	1.9
	Total	14.3	16.7	17.5	18.3	24.4	26.6
G	μ	1.5	1.5	2.5	0.5	1.3	0.5
	a	3.3	3.5	4.5	0.8	1.0	0.8
	pm	6.2	7.1	10.5	13.9	14.9	11.3
	b	5.1	6.4	2.7	5.8	5.8	10.6
	gvt	1.4	2.4	0.9	0.6	1.1	1.5
	Total	17.6	20.9	21.1	21.6	24.1	24.7
W+G		**31.9**	**37.6**	**38.6**	**39.9**	**48.5**	**51.3**

Notes: All results are reported using the mean of variance decomposition computed from 4 chains of 200,000 draws from the posterior distribution. We take average of the mean variance decomposition across all countries.

Table 1.10: Robustness check: GHH vs CRRA

(a)

		gy			gc		
		GHH	with m.e	CRRA	GHH	with m.e	CRRA
W	μ	9.3	9.2	6.2	4.3	4.7	6.7
	a	14.2	14.4	14.6	8.2	8.4	10.1
	pm	0.3	0.4	0.8	0.3	0.5	0.5
	b	1.0	1.6	0.7	2.7	3.4	1.3
	gvt	0.2	0.2	0.9	1.0	0.9	0.9
	Total	25.0	25.9	23.3	16.4	18.0	19.5
G	μ	7.9	7.4	7.3	3.9	3.9	8.4
	a	14.0	13.0	8.9	8.5	8.7	9.4
	pm	0.7	0.8	1.1	0.4	0.6	0.6
	b	1.6	3.1	1.2	6.1	5.9	1.9
	gvt	0.1	0.2	1.1	2.0	3.6	1.4
	Total	24.4	24.5	19.5	20.9	22.7	21.7
W+G		**49.4**	**50.4**	**42.8**	**37.3**	**40.7**	**41.1**

(b)

		gi			tby		
		GHH	with m.e	CRRA	GHH	with m.e	CRRA
W	μ	1.3	1.4	1.3	0.5	0.4	0.3
	a	3.1	2.9	6.8	0.5	0.3	0.5
	pm	5.3	6.3	3.7	7.6	13.3	18.0
	b	2.5	3.3	4.4	9.1	13.4	4.8
	gvt	2.2	2.0	1.1	0.7	0.4	0.4
	Total	14.3	15.9	17.3	18.3	27.9	24.0
G	μ	1.5	1.3	2.1	0.5	0.3	0.7
	a	3.3	2.8	2.3	0.8	0.4	0.9
	pm	6.2	7.4	5.8	13.9	10.8	14.0
	b	5.1	5.7	6.8	5.8	17.4	6.4
	gvt	1.4	1.2	0.1	0.6	0.4	0.1
	Total	17.6	18.4	17.0	21.6	29.3	22.1
W+G		**31.9**	**34.3**	**34.3**	**39.9**	**57.1**	**46.1**

Notes: All results are reported using the mean of variance decomposition computed from 4 chains of 200,000 draws from the posterior distribution. We take average of the mean variance decomposition across all countries for baseline model (GHH), baseline model with measurement error (with m.e.) and model with CRRA preferences (CRRA).

Chapter 2

Understanding the Cross Country Effects of U.S. Technology Shocks

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2.1 Introduction

It is widely documented that business cycles comove substantially across countries. Knowledge of how shocks transmit across countries is important to understand business cycles in each country and to design external policies. One potential explanation for the observed comovements across countries is endogenous transmission, i.e. shocks propagate from one country to another country through international trade in goods and financial assets. Yet, most existing models in the international business cycle literature are not able to generate significant endogenous transmission. International real business cycle models starting from Backus et al. (1992, 1995) generate weak correlation of key aggregate variables such as output and hours.To the extent that business cycles are correlated, it is because shocks driving business cycles are correlated. In particular, Schmitt-Grohé (1998) demonstrates that a class of real business cycle models cannot explain the observed dynamic effects of shocks to U.S. output on the Canadian economy through international trade and financial assets. Even in the more recent papers such as Engel and Wang (2011) and Johnson (2012), outputs across countries are only weakly correlated, suggesting that their models still do not generate substantial endogenous transmission. In the recent New Open Economy Macroeconomics (NOEM) literature, Justiniano and Preston (2010) find that estimated international business cycle models with nominal rigidities also fail to explain both the documented importance of U.S. shocks for Canadian business cycles and the comovements of macroeconomic variables between these two countries. Other papers using estimated NOEM models such as Adolfson et al. (2006, 2007) and Christiano et al. (2010) also report the similar result: namely that foreign shocks explain little of the domestic variables in their models. These results suggest that models with or without nominal rigidities fail to explain the observed cross-country comovements, especially when one looks beyond the second moments often used in this literature.

In this paper, we argue that a standard real international business cycle model augmented with three key features can generate substantial endogenous transmission of technology shocks and help to explain the observed business cycle comovements. The three key features are: Jaimovich-Rebelo preferences allowing for a low wealth elasticity of labor supply, variable capital utilization and imported intermediate inputs for production. We show that this augmented model is capable of explaining over 90% of the observed transmission of a permanent U.S. technology shock to Canadian output and hours worked. By contrast, a model without these three key features can only account for about 10% of the observed transmission.

The reason for why models without our three key features fail to generate substantial endogenous transmission is because they cannot explain the response of domestic hours to foreign shocks. The response of domestic hours plays a central role for the transmission of foreign shocks to the domestic economy because in the absence of a change in the level of domestic technology, increases in output require an increase in hours. When there is a positive permanent technology shock in the foreign country, the supply of foreign goods increases, causing the domestic terms of trade to appreciate. This appreciation of the domestic terms of trade affects both labor supply and labor demand in the domestic economy. In the standard model, on the labor supply side, domestic households become richer, and decrease their labor supply as in Panel (a) of Figure 2.1. On the labor demand side, for a given appreciation in the terms of trade, labor demand can increase. However, the shift in the labor demand curve is not sufficient to increase hours worked to generate strong endogenous transmission under plausible parameterizations of the standard model [1].

[1] Our key insight is that this relationship between domestic hours and the terms of trade does not depend on the elasticity of substitution between domestic and foreign goods, or the completeness of financial markets, both of which are often emphasized in the literature for transmission of technology shocks.

In contrast, the model with our three key features can generate substantial endogenous transmission. With Jaimovich Rebelo preferences, which allow for a low wealth elasticity of labor supply, the domestic labor supply curve does not shift substantially as in Panel (b) of Figure 2.1. On the labor demand side, for a given appreciation in the terms of trade, the increase in labor demand can be substantially larger when there are both imported intermediate inputs and variable capacity utilization. These two features increase the marginal product of labor. More specifically, domestic firms increase the amount of imported intermediate inputs from the foreign country given the cheaper price of imports, leading to an increase in labor demand. Additionally, variable capital utilization can shift the labor demand curve further to the right as it amplifies the change in other inputs in the production function. Therefore, in equilibrium, with our three key features, hours can increase significantly in the domestic economy as demonstrated in Panel (b) of Figure 2.1.

To test the ability of the model to generate endogenous transmission that is consistent with the data, we build an empirical benchmark that characterizes the transmission of shocks across countries. To that end, we document the effects of permanent U.S. technology shocks on the Canadian economy such as output, consumption, investment, hours, net export, and the terms of trade. We identify permanent U.S. technology shocks using the long run identification, which imposes that only permanent U.S. technology shocks can affect U.S. labor productivity in the long run. We find that this identified U.S. technology shock leads to a significant boom in Canada, where output in Canada increases as much as 60% of the increase in U.S. output. Also, hours worked in Canada increases with a similar magnitude as Canadian output, and Canadian terms of trade appreciate.

Given our empirical evidence, we analyze the endogenous transmission in our proposed model, and show that our model generates substantial endogenous transmission by estimating the model. More specifically, we demonstrate our intuition for how models with and without our three key features generate endogenous transmission using a simple calibration exercise. Then, we estimate the model using quasi-Bayesian methods by matching the theoretical impulse responses to a permanent U.S. technology shock with the corresponding empirical responses. This exercise demonstrates that our model can generate substantial endogenous transmission and match the observed transmission without exogenous correlation of technology shocks between the U.S. and Canada. Even when we allow for exogenous correlation of technology shocks, the data still prefer endogenous transmission, which is consistent with our empirical evidence. Furthermore, our estimation suggests that all three key features are necessary for the model's success.

Our insights about the transmission mechanism of technology shocks across countries are different from those proposed in the literature. For example, in Corsetti et al. (2008), the authors propose that the large wealth effect under incomplete markets is important to explain the transmission of technology shocks across countries. In another paper, Burstein et al. (2008) suggest that production sharing by using a low substitutability of domestic and foreign goods can increase the comovement of outputs across countries. However, these features are not able to explain the types of evidence that we have. We do not observe the movements of the terms of trade predicted in those theories. In Corsetti et al. (2008), endogenous transmission arises with the wealth effect channel only when the terms of trade in Canada depreciate and consumption actually decreases. In Burstein et al. (2008), a low elasticity of substitution helps only when the terms of trade in Canada appreciate a few times larger than the movements of hours. In the data, the Canadian terms of trade appreciates with a magnitude slightly larger than hours. Therefore, neither of the features proposed in these papers can create substantial endogenous transmission. Instead, we need our three key features to deliver the results consistent with our empirical findings.

Our insights above carry over to models with nominal rigidities, i.e. our three key features also help to generate substantial endogenous transmission with plausible parameterizations of nominal rigidities. To demonstrate that, we estimate a version of our model augmented with nominal rigidities by matching additionally the responses of Canadian inflation and nominal interest rate to a permanent U.S. technology shock. We find that when the model has our three key features, it can match the responses of aggregate variables in Canada under moderate nominal rigidities. Without these features, the estimated degree of price stickiness is close to one, meaning prices are fixed. The intuition for this result is as follows. In theory, price stickiness a la Calvo can generate time varying markups, which can shift the labor demand curve. If the markups in Canada decline in response to a positive U.S. technology shock, the demand for hours in Canada can increase and also inflation in Canada increases. In the data, a positive permanent U.S. technology shock has a negligible effect on inflation in Canada. Therefore, only when prices are almost fixed can markups vary sufficiently to help the model match hours without causing substantial inflation in Canada. In contrast, the three key features we propose can help the model to generate substantial endogenous transmission without relying heavily on the time varying markups, which is why the degree of price stickiness does not have to be so high in our case.

Our paper focuses on the transmission of technology shocks from the U.S. to Canada for the following reasons. First, we can address the large literature studying the transmission of technology shocks. Also, uncovering the endogenous transmission mechanism of technology shocks can give insights about that of other types of shocks. Another reason is that we can identify technology shocks using structural VAR without relying on specific structural models, and use this empirical evidence to test the ability of the model to generate endogenous transmission. Moreover, by focusing on the U.S. and Canada pair, we can treat the U.S. as the rest of the world to Canada since the U.S. accounts for over 70% of Canadian international trade. This assumption simplifies the analysis as there is no feedback effect from the U.S. to Canada. Lastly, previous papers fail to explain the relationship between these two countries, making it an interesting case to study.

To isolate the effects of shocks on Canadian variables without relying on specific structural model assumptions, we choose a limited information approach where we identify one type of shocks, i.e. permanent technology shocks, to characterize its transmission on Canada instead of using non-structural shocks or full information approach. The limited information approach has several advantages as follows. Cross-country comovements can be driven by a number of shocks, each of which can have an opposite effect on the international relative prices. For example, in theory, positive government spending shocks in the U.S. can depreciate Canadian terms of trade while positive U.S. technology shocks can appreciate Canadian terms of trade. Therefore, a non-structural U.S. shock that increases output in the U.S., which is a combination of these two types of shocks, can have ambiguous effects on Canadian terms of trade, leading to a wrong conclusion about endogenous transmission in the model. Furthermore, although full information approach can also identify structural shocks, identification relies on all aspects of assumptions in the model. In contrast, our empirical approach can help us test a wide range of models since we do not identify technology shocks using specific structural model assumptions. This is appealing for us since we can focus exclusively on the model's ability to generate endogenous transmission with a single benchmark.

The remainder of the paper is organized as follows. In Section 2, we document the effects of permanent U.S. technology shocks on Canada in the structural VAR. We present our baseline model in Section 3. Section 4 analyzes how our model with three key features generates substantial transmission from the U.S to Canada. We estimate our model and present the results in Section 5. We further elaborate what features are crucial for the success of the model in Section 6. Section 7 presents our robustness check to show that even when we allow exogenous correlation of technology shocks in the model to be estimated, the data assign a large role to endogenous transmission through international trade in generating comovement between the U.S. and Canada. Lastly, in Section 8, we extend our baseline model to add nominal rigidities into the model to show our three key features also help in this case and compare with the state of the art model in the New Open Economy Model literature. We conclude and suggest possible future work in Section 9.

2.2 Empirical Evidence

In this section, we document the effects of U.S. permanent technology shocks on Canadian economy using quarterly data for the U.S. and Canada post-Bretton Woods period between 1973Q1 and 2012Q3[2]. One of the reasons for our analysis to focus on the U.S. and Canada relationship is that we can consider the U.S. as the rest of the world to Canada. The U.S. and Canada have a tight trade linkages. In fact, the U.S. is Canada's single most important trading partner: For the last 30 years, the share of exports to the U.S. in total Canadian exports is, on average, over 75%, and that of imports is 68%, so U.S. shocks propagate to Canada through international trade directly and there is minimal indirect effects through a third country. Additionally, the U.S. is ten times larger than Canada. Therefore, we can assume that there is no feedback from the U.S..

2.2.1 The VAR Model

We estimate a VAR model with both U.S. and Canadian variables to identify US technology shocks using long run restrictions. The VAR has two blocks, a U.S. block, y_{1t}, and a Canadian block, y_{2t}. The U.S. block includes four variables: the growth rate of the labor productivity $\left(\Delta \ln \frac{y_t^{US}}{h_t^{US}}\right)$, the natural logarithm of hours $\left(\ln h_t^{US}\right)$, the growth rates of consumption and

[2]The data are from Statistics Canada, OECD National Accounts and Bureau of Labor Statistics.

investment $\left(\Delta \ln c_t^{US}, \Delta \ln I_t^{US}\right)$. The Canadian block includes six variables: the growth rates of output, consumption, and investment, the natural logarithm of hours, net exports and the growth rate of the terms of trade[3]. Throughout the paper, the terms of trade is defined as the ratio of price of imports to price of exports, so a decline in the terms of trade means appreciation.

Our identification strategy hinges on two assumption. First, Canada is relatively small compared to the U.S., having no effects on the U.S. block. More specifically, we impose a block exogeneity of the following form:

$$\begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$$

where the block exogeneity implies that

$$A_{12}(L) = 0 \text{ for } \forall L.$$

This assumption has also been placed in earlier works, for example, Schmitt-Grohé (1998) and Justiniano and Preston (2010) although they do not identify any particular structural shocks.

Second, we can identify U.S. permanent productivity shock from the U.S. block using long run restriction in Blanchard and Quah (1989) and Gali (1991), i.e. only permanent

[3]Our unit root and stationarity tests, which include the Augmented Dickey-Fuller and KPSS tests on all U.S. and Canadian variables, suggest that productivity, consumption, output, investment, and the terms of trade to be in difference. For the ADF tests, we cannot reject that U.S. output, consumption, investment, Canadian output, consumption, investment, and terms of trade have a unit root with a 10% significance level. For KPSS tests, we can reject trend stationarity for the same variables. Hours in the U.S. and Canada are kept in level as there is no strong evidence of non-stationarity and in the model, hours are stationary. Over-differencing, as suggested by Christiano, Eichenbaum and Vigfusson (2003) can cause model misspecification. In fact, Fisher (2006) also specifies hours in level in his empirical exercise. The results are similar if we use the ratio of consumption to output and investment to output instead.

technology shocks can affect U.S. labor productivity in the long run. This identification leads to the restriction that in this equation:

$$y_{1t} = \begin{bmatrix} \Delta \ln \frac{y_t^{US}}{h_t^{US}} \\ \begin{pmatrix} \ln h_t^{US} \\ \Delta \ln c_t^{US} \\ \Delta \ln I_t^{US} \end{pmatrix} \end{bmatrix} = \begin{bmatrix} C_{11}(L) & C_{12}(L) \\ C_{21}(L) & C_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t}^{US} \\ \varepsilon_{2t}^{US} \end{bmatrix},$$

$$C_{12}(1) = 0.$$

We include 4 lags of each of the variables and a constant in the VAR model.

Using the estimates of the VAR model above, we compute the impulse responses of the variables in the Canadian block, y_{2t}, following a one-standard deviation shock in ε_{1t}^{US}. The dynamic responses are invariant to the ordering of the variables within y_{2t}.

2.2.2 The VAR Result

The impulse response functions of all the variables for the U.S. are displayed in Figure 2.2 and in Canada in Figure 2.3. Lines marked with a plus sign correspond to the point estimate of the impulse responses, and the shaded areas are the 95% confidence band calculated from bootstrapping 1,000 times[4].

Our result suggests that after a positive U.S. permanent technology shock occurs in period 1,

[4]The bootstrap procedure is as follows: from the centered residuals of the estimation, bootstrap residuals are generated by randomly drawing with replacement. These quantities are used to compute bootstrap time series, which is then re-estimated. The percentile interval is determined as $\left[\widehat{IR} - t^*_{0.025}, \widehat{IR} - t^*_{0.975}\right]$ where $t^*_{0.975}, t^*_{0.025}$ are the 0.975 and 0.025 quantiles, respectively, of the distribution of the centered bootstrap IR (Hall's percentile confidence interval).

(1) U.S. output, consumption, investment and hours increase[5].

(2) All of the Canadian aggregate quantities go up and the terms of trade appreciates (falls).

(3) In terms of the relative magnitude, Figure 2.4 shows that output in Canada increases as much as 60% of the increase in the U.S. at the maximum. Investment increases on impact, reaching the highest response of about twice as much as output. Consumption also increases but less than output. Canadian terms of trade appreciate slightly more than Canadian output. Net exports to output ratio in Canada increases significantly. The maximum response of net exports is about half of Canadian output.

(4) Labor productivity increases slightly, about a fourth of Canadian output, but not significant at 95% confidence level.

These results are different from Schmitt-Grohé (1998) who finds that the terms of trade in Canada does not move at all in response to an innovation to U.S. output. One potential explanation for this difference is that the innovation in U.S. output may includes other types of shocks that have opposite effects on the terms of trade. For example, a calibrated model in Backus et al. (1994) suggests that while a technology shock in the U.S. causes Canadian terms of trade to appreciate, a government spending shock in the U.S. can cause Canadian terms of trade to depreciate. Therefore, in response to an innovation to U.S. output, the terms of trade may not change significantly. Focusing on only permanent technology shocks helps us to avoid this problem.

To gauge the importance of U.S. technology shocks to Canada, we perform a forecast error variance decomposition of these shocks on Canadian variables. As summarized in Table 2.1, the identified U.S. shocks explain a sizable fraction of business cycles in Canada, but not 100% which is why we focus on the conditional responses. In particular, U.S. technology shocks

[5]On impact, response of hours is close to zero and insignificant.

contribute significantly to the fluctuations of all real variables, up to 39% of the Canadian output and 24% of hours at eight-quarter horizon. The contribution to consumption in Canada is smaller, about 26% at eight-quarter horizon and 35% at 20-quarter horizon. Only about 14% of investment and 19% the terms of trade variation are explained by this U.S. permanent technology shock at 20-quarter horizon, suggesting that the high volatility of these variables is caused by some other factors.

These results are robust to other VAR specifications and data. For example, we find a significant increase in both output and hours in Canada in response to a U.S. permanent technology shocks identified from U.S. productivity and hours data in the manufacturing sector, similar to Corsetti et al. (2008). This result also holds if we use a measure of total factor productivity from Fernald (2012) for the U.S. instead of labor productivity, or real exchange rate instead of the terms of trade in the specification. Also, when we use non-fuel terms of trade in the VAR, we find that this measure of terms of trade exhibit the same pattern as the standard terms of trade measure, which decreases significantly after a positive U.S. permanent technology shocks. Besides, real exports and imports of machineries, automotive and industrial goods in Canada are most affected by this U.S. shock compared to energy products. This result suggests that the shocks we recover are not oil price shocks[6]. Finally, we get the similar response in terms of relative magnitude when we run the same specification for the U.S. and Mexico.

2.2.3 The U.S. and Canadian Technology Processes

Are the effects of U.S. permanent technology shocks on Canada documented above a product of technology spillover? One way to empirically diagnose if U.S. and Canadian technology

[6]Oil price can be an important factor explaining the overall movements of Canadian terms of trade but not the conditional responses that we focus on.

shocks are mostly common is to compute the correlation between U.S. and Canadian identified permanent technology shocks. To this end, we apply the same long run identification above to Canadian labor productivity growth, hours, consumption and investment growth rates to extract Canadian permanent technology shocks. The correlation between this identified shock and that of the U.S. turns out to be negative and insignificant contemporaneously (-0.07) and only significant and positive at lag six and negative for lag nine[7]. In other words, there is little evidence that there is a strong exogenous correlation component in the shock processes of these two countries in the short run.

Technology can also be spillover directly and gradually if there is some cointegrating relationship between the U.S. and Canada. To check this possibility, we run cointegration tests for outputs in both countries. Table 2.2 report the results from the unrestricted cointegration rank test using the trace and maximum eigenvalue methods as Johansen (1991) with four lags and a constant in the cointegrating vector. The trace statistics are less than the 5% critical values (15.41 and 3.76, respectively) for both zero and one cointegrating vector, and similarly, max eigenvalue statistics are less than the 5% critical value. In other words, there is no strong evidence supporting either cointegration or not between U.S. and Canadian output.

These results suggest that the strong comovement between the U.S. and Canada in response to a U.S. technology shock should, to some extent, comes from international goods and financial trades rather than only correlated shocks. Nevertheless, to quantify how large the role of spillover is compared with transmission through international trade, we model below a cointegrating relationship in the technology process and let the data decide how large the role of this propagation of technology between the U.S. and Canada is.

[7] The five quarters centered moving average of the U.S. and Canadian shocks are positively but insignificantly correlated contemporaneously and up to 5 lags (0.10).

2.3 The Model

This section details our baseline model, which builds on Backus, Kehoe and Kydland (1992, 1995) models. We treat Canada as a small open economy and the U.S. as a large closed economy. In other words, Canada plays no role in explaining U.S. aggregate variables. Our model assumes incomplete financial markets where agents can only trade one-period non-contingent bonds. The model also includes two other frictions often used in the literature, namely investment adjustment cost and debt elastic interest rate.

Our main departure from standard international real business cycle models is that we include three features in the model. These three key features are Jaimovich-Rebelo utility function, variable capital utilization, and imported intermediate inputs. These features, as we show later, are key to generating sufficiently strong endogenous transmission of technology shocks across countries. Moreover, we also show that all three key features are necessary to deliver substantial transmission through international trade as they interact with each other.

Since U.S. economy is similar to Canada, we describe below the structure of the Canadian economy. For ease of notation, Canada is denoted as country 1 in the model.

2.3.1 Households

Households in each country maximize the expected lifetime utility:

$$\max E_0 \sum_{t=0}^{\infty} \beta^t \frac{\left[C_{1t} - \phi_1^H \frac{1}{1+\frac{1}{v}} X_{1t} H_{1t}^{1+\frac{1}{v}}\right]^{1-\sigma} - 1}{1-\sigma}$$

where C_{1t} is consumption , H_{1t} is hours worked and the parameter $\beta \in (0,1)$ denotes the subjective discount factor. The subscript 1 denotes country 1, σ is intertemporal elasticity of substitution. $v > 0$ is related with Frisch elasticity of labor supply. X_{1t} satisfies the following equation:

$$X_{1t} = (C_{1t})^{\kappa_1} X_{1t-1}^{1-\kappa_1}. \tag{2.1}$$

This preference specification is due to Jaimovich-Rebelo (2009), featuring the parameter κ_1 that governs the wealth elasticity of labor supply. This parameter is estimated to understand the transmission mechanism. When $\kappa_1 = 1$, the preference is the common CRRA utility function characterized by King, Plosser, and Rebelo (1988, KPR henceforth). As $\kappa_1 \to 0$, the utility function becomes linear in consumption and hours worked, which is the Greenwood, Hercowitz, and Huffman (1988, GHH henceforth) preferences. In that case, there is no wealth effect on the labor supply decision.

We assume that households can only borrow with one period non-contingent bonds denominated in foreign consumption, B_{1t+1}^F, paid with interest rate R_{1t}^F. To ensure a well-defined steady state and stationarity in the model, we assume debt elastic interest rate of the form,

$$R_{1t}^F = R_{2t}^F A\left(q_t B_{t+1}^F \frac{1}{Z_{1t}}\right)$$

where R_{1t}^F is interest rate which country 1 needs to pay and R_2^F is interest rate in country 2. $q_t B_{1t+1}^F \frac{1}{Z_{1t}}$ is a real foreign asset position where q_t is the real exchange rate, which is the relative price of foreign consumption goods in terms of home consumption goods and the term Z_{1t} is technology level in country 1. Following Schmitt-Grohé and Uribe (2003) and Adolfson et al. (2007), we assume that A is given by:

$$A\left(q_t B_{t+1}^F \frac{1}{Z_{1t}}\right) = \exp\left[-\phi_1^B\left(\frac{q_t \frac{B_{t+1}^F}{Z_{1t}}}{\left(\frac{q_t B_{t+1}^F}{Z_{1t}}\right)_{ss}} - 1\right)\right]$$

where $\left(\frac{q_t B_{t+1}^F}{Z_{1t}}\right)_{ss}$ is the steady state value of real foreign asset position.

Household is assumed to own capital K_{1t}, which evolves over time under the following law of motion:

$$K_{1t+1} = (1-\delta) K_{1t} + I_{1t} \left(1 - S\left(\frac{I_{1t}}{I_{1t-1}}\right)\right) \tag{2.2}$$

where δ is the depreciation rate of capital and I_t is the gross investment. Following Christiano et al. (2005), we assume that it is costly to adjust the level of investment for capital, i.e. $S(.)$ is the adjustment cost satisfying $S(\mu_1) = 0,\ S^{'}(\mu_1) = 0,\ S^{''}(\mu_1) = s_1$, where μ_1 is the steady state growth rate of output. We use the standard quadratic specification of S:

$$S\left(\frac{I_{1t}}{I_{1t-1}}\right) = \frac{s_1}{2}\left(\frac{I_{1t}}{I_{1t-1}} - \mu_1\right)^2.$$

In addition, household has to pay a utilization cost $a(u_{1t})$ for the intensive use of capital K_{1t} in terms of consumption unit. The capital utilization, u_{1t}, has an increasing and convex cost $a(u_{1t})$ per unit of capital. We adopt a quadratic function for a as follows:

$$a(u_{1t}) = a_{11}(u_{1t} - 1) + \frac{a_{21}}{2}(u_{1t} - 1)^2$$

with $a_{11}, a_{21} > 0$. The parameter a_{21} is the sensitivity of the utilization cost to variation in the rental rate of capital. The parameter a_{11} governs the steady state level of u_{1t}.

The household budget constraint is then:

$$\begin{aligned} & C_{1t} + p_{1t}^I I_{1t} + B_{1t+1}^D \frac{1}{R_t^D} + q_t B_{1t+1}^F \frac{1}{R_{1t}^F} \\ \leq\ & W_{1t} H_{1t} + R_{1t}^k (u_{1t} K_{1t}) + B_{1t}^D + q_t B_{1t}^F - a(u_{1t}) K_{1t} \end{aligned} \tag{2.3}$$

where p_t^I is the relative price of investment goods in terms of consumption goods. B_{1t+1}^D is the domestic bond with interest rate R_t^D , W_{1t} is the real wage, and R_{1t}^k is the real return to capital in terms of home consumption goods unit.

Intermediate Good Producer

The intermediate good producer in country 1 specializes in the production of home goods Y_t^D by combining capital service, $u_{1t}K_{1t}$, labor, H_{1t}, and imported and domestic intermediate inputs, M_{21t} and M_{11t}, respectively, using the production function

$$Y_t^D = \left((u_{1t}K_{1t})^{\alpha} (Z_{1t}H_{1t})^{1-\alpha}\right)^{1-\alpha_{11}-\alpha_{21}} M(M_{11t}, M_{21t}), \tag{2.4}$$

where $\alpha_{11} > 0$ and $\alpha_{21} > 0$ are the shares of domestic and imported intermediate inputs in gross output, respectively, $\alpha(1-\alpha_{11}-\alpha_{21}) > 0$ is the capital share, and $M(M_{11t}, M_{21t})$ is the composite of home and imported intermediate good as we assume that the intermediate good producer uses both its output for intermediate input (M_{11t}) and imported intermediate input (M_{21t}). Roundabout production is introduced to capture the role of intermediate inputs in production and cross border trade. The functional form of $M(.)$ is given as follows:

$$M_t = \left((\alpha_{11})^{\frac{1}{\gamma_1^m}} (M_{11t})^{\frac{\gamma_1^m-1}{\gamma_1^m}} + (\alpha_{21})^{\frac{1}{\gamma_1^m}} (M_{21t})^{\frac{\gamma_1^m-1}{\gamma_1^m}}\right)^{\frac{\gamma_1^m}{\gamma_1^m-1}}. \tag{2.5}$$

The goods produced domestically, Y_t^D, can be sold to domestic final good producer to make domestic consumption goods, D_{1t}^C, domestic investment goods, D_{1t}^I, or be used for domestic good production, M_{11t}, or sold to foreign producers to make foreign consumption goods, D_{2t}^C, foreign investment goods, D_{2t}^I, or be used in their production, M_{12t}.

Therefore, the intermediate good producer's problem is choosing labor, capital service, domestic and foreign inputs to maximize its profit measured in consumption goods unit Π_{1t}:

$$\Pi_{1t} = p_{1t}^D Y_{1t}^D - \left[\left(W_{1t}H_{1t} + R_{1t}^k (u_{1t}K_{1t})\right) + \left(p_{1t}^D M_{11t} + p_{1t}^F M_{21t}\right)\right] \tag{2.6}$$

subject to the above production function, where p^D_{1t} and p^F_{1t} are the prices of domestic and foreign intermediate goods in the domestic market relative to final consumption good price P_{1t}, which is defined below.

Final Good Producer

The final good producer in the small open economy imports foreign consumption F^C_{1t} and investment F^I_{1t} goods from foreign producer at price P^F_{1t}. The final good producer also buys domestic consumption D^C_{1t} and investment D^I_{1t} input from the intermediate good producer at price P^D_{1t}. We assume that the law of one price holds.

The final good producer combines the domestic inputs, D^C_{1t}, and foreign inputs, F^C_{1t} to produce final consumption using the following aggregator:

$$C_{1t} = \left(\left(\omega^C_1\right)^{\frac{1}{\gamma^C_1}} \left(D^C_{1t}\right)^{\frac{\gamma^C_1 - 1}{\gamma^C_1}} + \left(1 - \omega^C_1\right)^{\frac{1}{\gamma^C_1}} \left(F^C_{1t}\right)^{\frac{\gamma^C_1 - 1}{\gamma^C_1}} \right)^{\frac{\gamma^C_1}{\gamma^C_1 - 1}} \tag{2.7}$$

where $\omega^C_1 > 0$ is the home bias parameter for consumption goods, and γ^C_1 is the elasticity of substitution between home and foreign consumption goods. The final consumption good price is then defined as follows:

$$P_{1t} = \left(\omega^C_1 \left(P^D_{1t}\right)^{1-\gamma^C_1} + \left(1 - \omega^C_1\right) \left(P^F_{1t}\right)^{1-\gamma^C_1} \right)^{\frac{1}{1-\gamma^C_1}}.$$

The final good producer also produces investment goods in the same way as consumption goods, i.e.:

$$I_{1t} = \left(\left(\omega^I_1\right)^{\frac{1}{\gamma^I_1}} \left(D^I_{1t}\right)^{\frac{\gamma^I_1 - 1}{\gamma^I_1}} + \left(1 - \omega^I_1\right)^{\frac{1}{\gamma^I_1}} \left(F^I_{1t}\right)^{\frac{\gamma^I_1 - 1}{\gamma^I_1}} \right)^{\frac{\gamma^I_1}{\gamma^I_1 - 1}}$$

where $\omega_1^I > 0$ is the home bias parameter for investment goods and γ_1^I is the elasticity of substitution between home and foreign investment goods. Similar to the price of consumption goods, the investment good price is

$$P_{1t}^I = \left(\omega_1^I \left(P_{1t}^D\right)^{1-\gamma_1^I} + \left(1-\omega_1^I\right)\left(P_{1t}^F\right)^{1-\gamma_1^I}\right)^{\frac{1}{1-\gamma_1^I}}$$

The final good producer then sells consumption C_{1t} and investment I_{1t} to households. The final good producer's problem is, then, to choose domestic and foreign inputs to maximize his profits, which yields the following set of demands for each domestic and foreign consumption and investment goods:

$$\begin{aligned} D_{1t}^C &= \omega_1^C \left(p_{1t}^D\right)^{-\gamma_1^C} C_{1t}, & D_{1t}^I &= \omega_1^I \left(\frac{p_{1t}^D}{p_{1t}^I}\right)^{-\gamma_1^I} I_{1t}, \\ F_{1t}^C &= \left(1-\omega_1^C\right)\left(p_{1t}^F\right)^{-\gamma_1^C} C_{1t}, & F_{1t}^I &= \left(1-\omega_1^I\right)\left(\frac{p_{1t}^F}{p_{1t}^I}\right)^{-\gamma_1^I} I_{1t}. \end{aligned}$$

2.3.2 Technology Process

Given our empirical evidence above, we follow Rabanal et al. (2011) and assume that there is a cointegrating relationship between Canadian and U.S. technology. However, the difference between our specification and that of Rabanal el al. (2011) is that we allow for a contemporaneous effect of U.S. shocks on Canada through the correlation of shocks. Additionally, there is no feedback from Canada to the U.S.. The technology process for Canada is then described by:

$$\Delta \ln Z_{1t} = \mu_1 + \zeta\left[\ln Z_{2t-1} - \ln Z_{1t-1}\right] + e_{1t}. \tag{2.8}$$

When technology differential $\frac{Z_{2t-1}}{Z_{1t-1}}$ is smaller than the long run value, $\zeta > 0$ ensures that $\Delta \ln Z_{1t}$ will increase eventually so that we obtain a balanced growth path. Our representation implies that $\Delta \ln Z_{1t}$ and $\frac{Z_{2t}}{Z_{1t}}$ are stationary processes and ζ governs the speed at which technology ratio $\frac{Z_{2t}}{Z_{1t}}$ goes back to the long run value.

For the U.S., which is assumed to be closed, the technology growth rate follows an AR(1) process as follows:

$$\Delta \ln Z_{2t} = \mu_2 + \rho_2 \Delta \ln Z_{2t-1} + e_{2t}. \tag{2.9}$$

The innovations of technology for the U.S. and Canada, e_{1t} and e_{2t}, respectively, have the following relationship:

$$\begin{pmatrix} e_{1t} \\ e_{2t} \end{pmatrix} = A \begin{pmatrix} v_{1t} \\ v_{2t} \end{pmatrix}, v_t \sim N(0, I), \text{ and } A \equiv \begin{pmatrix} \bullet & \tau\sigma_2 \\ \bullet & \sigma_2 \end{pmatrix},$$

where τ measures the magnitude of impact of shock in the U.S. on Canada. As the purpose of the paper is to understand U.S. shocks affecting Canada, we ignore the first column of the matrix A.

2.3.3 Prices and Equilibrium

The optimal conditions for domestic and foreign bond holdings imply an uncovered interest rate parity condition placing a restriction on the movements of the domestic interest rate. As the terms of trade is defined as

$$TOT_t = \frac{p_{1t}^F}{p_{1t}^D}, \tag{2.10}$$

and we normalize $P_{2t} = P_{2t}^F = 1$, then the law of one price dictates that $p_{1t}^F = q_t$.

With intermediate goods in gross output, we define GDP as gross output subtracting intermediate inputs at the steady state prices:

$$GDP_{1t} = Y_t^D - M_{11t} - M_{21t}.$$

Country 2 produces gross output Y_t^F so their GDP is defined analogously:

$$GDP_{2t} = Y_t^F - M_{22t}.$$

The model is closed with the demands of home consumption D_{2t}^C, investment D_{2t}^I and intermediate M_{12t} goods from foreign country given exogenously to Canada by the following equations:

$$D_{2t}^C = \left(1-\omega_2^C\right)\left(\frac{p_{1t}^D}{q_t}\right)^{-\gamma_2^C} C_{2t} \tag{2.11}$$

$$D_{2t}^I = \left(1-\omega_2^I\right)\left(\frac{p_{1t}^D}{q_t}\right)^{-\gamma_2^I} I_{2t} \tag{2.12}$$

$$M_{12t} = \frac{\alpha_{12}}{\alpha_{22}}\left(\frac{p_{1t}^D}{q_t}\right)^{-\gamma_2^m} M_{22t} \tag{2.13}$$

where ω_2^C and ω_2^I are the home biases of consumption and investment goods in the U.S., γ_2^C, γ_2^I and $\gamma_2^m > 0$ are the elasticities of substitution between home and foreign country consumption, investment and intermediate goods in the U.S., and C_{2t}, I_{2t}, M_{22t} are consumption, investment and domestic intermediate inputs in country 2, respectively.

Finally, the general equilibrium requires that all markets clear, i.e.:

$$D_{1t}^C + D_{1t}^I + D_{2t}^C + D_{2t}^I + M_{12t} + M_{11t} = Y_t^D \tag{2.14}$$

$$C_{2t} + I_{2t} + M_{22t} = Y_t^F. \tag{2.15}$$

2.4 Understanding the Transmission Mechanism

Before formally estimating the model, we explain in this section how our model can generate substantial transmission of shocks through international trade. To this end, we first show how standard international business cycle models without our three key features fail to explain the data. Then, we discuss how our three key features help to reconcile the model with the data.

2.4.1 The Failure of Standard Models

Standard models such as Backus et al. (1994), Corsetti et al. (2008), Burstein et al. (2008) are not able to generate substantial endogenous transmission in the data. We show that in these models, a positive technology shock can only generate transmission through international trade under unreasonable parameter values. To that end, we analyze a variation of our model that is similar to standard international business cycle models. More specifically, we shut down our three key features presented in the baseline model, i.e. household has the standard King-Plosser-Rebelo preference, there is no variable capacity utilization, and there is no imported intermediate inputs.

Our analysis focuses on the response of domestic hours as hours play a central role in the transmission of the foreign shock . In the absence of a change in the level of domestic technology, increases in output require an increase in hours. To investigate the quantitative aspects of the model, we log-linearize and combine the following equilibrium conditions on labor demand, labor supply and domestic price level:

$$\frac{-\frac{\partial U_t}{\partial H_{1t}}}{\frac{\partial U_t}{\partial C_{1t}}} = W_{1t} \tag{2.16}$$

$$p_{1t}^D \frac{\partial F}{\partial H_{1t}} = W_{1t} \tag{2.17}$$

$$\left(p_{1t}^D\right)^{\gamma_1^C} = \left[\omega_1^C + \left(1-\omega_1^C\right)\left(TOT_t\right)^{\gamma_1^C}\right]^{-\frac{1}{\gamma_1^C}}. \tag{2.18}$$

Then, the log deviation of hours can be written as a function of the change in the terms of trade, consumption, technology and capital as follows:[8]:

$$\widehat{H_{1t}} = \frac{1}{\alpha + \frac{1}{v}} \left[-\widehat{C}_{1t} - \left(1 - \omega_1^C\right) \widehat{TOT}_t + (1-\alpha)\widehat{Z}_{1t} + \alpha \widehat{K}_{1t} \right] \tag{2.19}$$

This equation allows us to decompose the movement of hours in the domestic economy into four components: the wealth effect from the change in consumption, the terms of trade effect, the effect from domestic technology change and the capital accumulation effect. To further simplify our analysis, we ignore the effect of capital accumulation since it is not quantitatively important in the short run[9]. Therefore, when there is no exogenous correlation of technology shocks, i.e. $Z_{1t} = 0$, hours in the domestic economy can increase only if

$$\widehat{C_{1t}} < -\left(1 - \omega_1^C\right) \widehat{TOT_t}$$

To match a 0.5% increase in consumption and a 1% appreciation of the terms of trade found

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[8]To derive this equation, we assume a standard King-Plosser-Rebelo preferences, $U(C_t, H_t) = \frac{C_t^{1-\sigma}}{1-\sigma} V(H)$ where $V(H) = \exp\left(1 - \phi_H \frac{1}{1+\frac{1}{v}} H_t^{1+\frac{1}{v}}\right)^{1-\sigma}$.

If we assume utility function as in Backus et al. (1994), then $U = \frac{\left(C^{\mu}(1-H)^{1-\mu}\right)^{1-\sigma}}{1-\sigma}$, we get

$$\widehat{H_{1t}} = \frac{1}{\alpha + \frac{H}{1-H}} \left[-\widehat{C}_{1t} - \left(1 - \omega_1^C\right) \widehat{TOT}_t + (1-\alpha)\widehat{Z}_{1t} + \alpha \widehat{K}_{1t} \right]$$

With separable utility function $U = \frac{C^{1-\sigma}}{1-\sigma} - \phi_H \frac{H^{1+\frac{1}{v}}}{1+\frac{1}{v}}$, we get

$$\widehat{H_{1t}} = \frac{1}{\alpha + \frac{1}{v}} \left[-\sigma\widehat{C}_{1t} - \left(1 - \omega_1^C\right) \widehat{TOT}_t + (1-\alpha)\widehat{Z}_{1t} + \alpha \widehat{K}_{1t} \right]$$

[9]The capital accumulation equation implies that

$$\widehat{K}_{t+j} = (1-\delta)^j \underset{(=0)}{\widehat{K}_t} + \delta \left[\widehat{I}_{t+j-1} + ... + (1-\delta)^{j-1} \widehat{I}_t \right]$$

Assuming there is a 1% permanent increase in investment until period j, then $\widehat{K}_{t+j} = 0.01 \left[1 - (1-\delta)^j\right]$ means that it takes approximately 30 periods for capital to increase by 0.5%.

in VAR, i.e. the terms of trade decreases by 1%, standard models require that $\omega_1^C < 0.5$ to get a positive response of hours. However, ω_1^C is interpreted as the home bias parameter, which is often calibrated using the share of domestic goods in total consumption. In the case of Canada, $\omega_1^C = 0.9$. In other words, standard models without our three key features cannot generate an increase in hours in Canada under reasonable parameterization. To see this point in a different way, when we calibrate $\omega_1^C = 0.9$ for Canada, the above condition means hours in Canada can increase only if $\widehat{C_{1t}} < -0.1\widehat{TOT_t}$. From our VAR results, the increase in consumption is more than 10% of the appreciation in the terms of trade, which implies that hours decrease.

Our intuition for the above result is through the movements in both labor demand and the labor supply. In the labor supply side, an appreciation in the terms of trade causes an increase in consumption, leading to a decline in labor supply due to a strong wealth effect. In the labor demand side, an appreciation in the terms of trade can shift the labor demand curve to the extent households import consumption goods. However, this shift in the labor demand curve is quantitatively small because the share of imported consumption goods is about 10% of total consumption in Canada. Therefore, in equilibrium, hours in Canada fall.

An important insight that we provide in this paper is that our result above does not depend on many features that have been highlighted to be important in the previous literature. For example, v, the labor supply elasticity parameter with respect to real wage under the assumed utility function, does not play a crucial role in determining the movement of hours. More importantly, unlike Corsetti et al. (2008) and Enders and Muller (2009) who emphasize incomplete financial markets as an important feature of the transmission mechanism of technology shocks, we find that market completeness does not alter the relationship of hours and the terms of trade as shown in equation (19). Additionally, this relationship does not depend on the elasticity of substitution, γ_1 in the sense that given the movements of the terms of trade and consumption, the movements of hours are determined regardless of the elasticity of substitution. The reason we have a different conclusion compared to Corsetti et al. (2008) or Enders and Muller (2009) is as follows. In Corsetti et al. (2008), incomplete markets together with a large elasticity of substitution can generate endogenous transmission because there is a depreciation in the terms of trade for Canada and a decrease in consumption. However, we observe an increase in consumption and an appreciation in the terms of trade for Canada in the data, which implies that their mechanism does not work.

The fact that our result does not directly depend on the elasticity of substitution, γ_1 also implies that a small elasticity of substitution, as suggested by Burstein et al. (2008), is not a remedy to generate substantial comovement across countries. In Burstein et al. (2008), production sharing which can be interpreted as a small elasticity of substitution can increase the output comovement across countries. However, equation (19) implies that once we account for the movement of the terms of trade, the relationship between hours and the terms of trade does not depend on the elasticity of substitution parameter. In other words, when the elasticity of substitution is small, the model can generate an increase in hours worked but at the expense of a large appreciation in the terms of trade that are several times larger than what is observed empirically. Therefore, if we try to match the joint movements of consumption, hours and the terms of trade, changing the elasticity of substitution does not work.

Our above analysis shows that standard international business cycle models, and those with fixes in terms of financial market completeness or elasticity of substitutions across domestic and foreign goods, are not able to generate strong endogenous transmission through international trade.

2.4.2 How Our Model Works

We now discuss how the model with three key features that we propose works. More specifically, we show that the three key features, Jaimovich-Rebelo preferences, imported intermediate inputs and variable capital utilization, interact with each other to generate substantial endogenous transmission through international trade.

Jaimovich-Rebelo Preferences

Jaimovich-Rebelo preference specification is an important feature to adjust the strength of the wealth effect on labor supply. Intuitively, one reason for the failure of the standard models is the strong wealth effect that reduces labor supply. As we show above, since Canadian households become wealthier after a U.S. permanent technology shock, they increase consumption. This increase in consumption causes hours in Canada to decrease, resulting in a negative comovement of hours between the two countries. Therefore, unless the shift in the labor demand curve is sufficiently large, the model requires a small wealth effect on labor supply so that hours can increase in equilibrium.

To illustrate the intuition above, we analyze the relationship between hours and the terms of trade assuming that there is no wealth effect on labor supply. To that end, we assume that $\kappa_1 = 0$ in our model. Furthermore, we assume that this is the only feature added to standard models. Then, we can rewrite equation (19) as follows:

$$\widehat{H}_{1t} = \frac{1}{\alpha + \frac{1}{v}} \left[-\left(1 - \omega_1^C\right) \widehat{TOT}_t + (1-\alpha)\, \widehat{Z}_{1t} + \alpha \widehat{K}_{1t} \right]. \tag{2.20}$$

Since consumption does not appear in this equation, Canadian hours can go up without any change in technology and capital as long as the terms of trade appreciate. In other words, shutting down wealth effect can help increase endogenous transmission within the model.

However, the fact that hours increase does not translate to substantial endogenous transmission. To illustrate this point, we calculate the responses of hours when there is a 1% appreciation in the terms of trade and there is no wealth effect on labor supply. Using the calibrated parameters for Canada and the U.S. presented in Table 2.3 which we discuss in the Estimation section, we find that there is only an increase of 0.1% in hours when the terms of trade appreciates by 1% as

$$\widehat{H}_{1t} = -\frac{1}{\alpha + \frac{1}{v}} \left(1 - \omega_1^C\right) \widehat{TOT}_t \simeq -0.1\widehat{TOT}_t.$$

We document above that the response of hours is only slightly smaller than that of the terms of trade, which means that quantitatively a preference specification with no wealth effect only *cannot* solve the problem of weak endogenous transmission. The reason is that the modification of the household preferences prevents labor supply from declining while it has no effect on the increase in labor demand, which is not sufficiently large. Therefore, this preference specification which affects the strength of the wealth effect on labor supply is not sufficient to generate substantial transmission through international trade.

Imported Intermediate Inputs

The second key feature is imported intermediate inputs, whose role is to push labor demand to respond more strongly to the movement of the relative price of domestic goods. The first order condition for imported intermediate goods is given by:

$$\frac{\partial F}{\partial M_{21t}} = \frac{p_t^F}{p_t^D} = TOT_t,$$

which means that intermediate goods import increases when the relative price becomes cheaper. Since the marginal product of labor is increasing in imported intermediate goods, change in the relative price shifts the labor demand curve. To see this, we combine firms' optimality conditions to have the following relationship:

$$\widehat{H}_{1t} = \frac{1}{\alpha + \frac{1}{v}} \left(- \left[\left(1 - \omega_1^C\right) + \frac{\alpha_{21}}{1 - \alpha_{11} - \alpha_{21}} \right] \widehat{TOT}_t + (1 - \alpha)\, \widehat{Z}_{1t} + \alpha \widehat{K}_{1t} \right), \tag{2.21}$$

where we assume again that there is no wealth effect on labor supply for simplicity. Compared to equation (20), equation (21) has an additional term for the terms of trade, which is $-\frac{1}{\alpha+\frac{1}{v}}\frac{\alpha_{21}}{1-\alpha_{11}-\alpha_{21}}$. This term reflects the effects of imported intermediate goods on labor demand.

Quantitatively, imported intermediate inputs can play an important role in generating substantial increase in hours in Canada. Under the calibrated parameters for Canada, hours would increase up to 0.26% with imported intermediate inputs in response to a 1% appreciation in the terms of trade, compared to 0.1% without imported intermediate inputs. In other words, the presence of imported intermediate goods can more than doubles the response of hours to the terms of trade.

Variable Capacity Utilization

The third key feature of the model, variable capacity utilization, is important as it amplifies the effects of both direct and indirect effects of the change in the terms of trade on hours worked. To see this, the first order condition describing the relationship between hours and utilization and the domestic goods prices, assuming again that there is no wealth effect on the labor supply for simplicity:

$$\phi_H H_t^{\frac{1}{v}} = p_t^D \left(1 - \alpha\right) \left(u_t K_t\right)^{\alpha} \left(Z_t H_t\right)^{-\alpha}.$$

implies that an increase in utilization shifts the labor demand curve and increases hours. Furthermore, combining the first order conditions, we obtain

$$\frac{\phi_H H_t^{\frac{1}{v}}}{a'(u_t)} = \frac{1-\alpha}{\alpha} \frac{u_t K_t}{Z_t H_t},$$

which implies that utilization is an increasing function in hours given the level of capital and technology. In other words, utilization moves in the same direction as hours, and thereby amplifies the effects of other factors on hours[10].

To gauge how large the amplification of variable capital utilization can have on hours in Canada, we calculate the magnitude of the responses of hours to a 1% increase in the terms of trade assuming that $\left(\frac{a_1}{a_2}\right)_1 = 0.08$, i.e. there is a high elasticity of utilization with respect to return. As hours can be expressed in terms of the terms of trade and cost of utilization as follows:

$$\left(\alpha \frac{\left(\frac{a_1}{a_2}\right)_1}{1+\left(\frac{a_1}{a_2}\right)_1} + \frac{1}{v}\left(1 - \frac{\alpha}{1+\left(\frac{a_1}{a_2}\right)_1}\right)\right)\widehat{H}_{1t} = -\left(1-\omega_1^C\right)\widehat{TOT}_t + ...,$$

where "..." stands for the terms for technology and capital accumulation, we find that hours would increase by 0.23% compared to 0.1% without utilization. This simple exercise demonstrates that utilization can be an important factor as it helps to double the response of hours to the movements of the terms of trade.

Our simple exercises above also show that one or two features *only* is *not* capable of generating substantial transmission through international trade. In fact, we need all three of them as they interact with each other to generate about 0.62% increase in hours worked

[10]With a different utilization cost specification such as $K_{t+1} = (1-\delta(u_t)) K_t + I_t$, as in Schmitt-Grohé and Uribe (2012), the amplification effect of utilization may be weaker. The reason is that the value of capital can increase, which increases the cost of utilization and reduces the response of utilization.

in Canada for a 1% appreciation in the terms of trade, which is similar to what we find in the data. Nevertheless, we let the data speak by formally estimating the model in the next section.

2.5 Estimation

This section quantitatively evaluates the ability of our model to generate substantial transmission through international trade. To that end, we first explain our estimation method, then present the main results of the paper. More specifically, we show that our model matches over 90% of the VAR evidence presented above. In contrast, without our three key features, the model can match less than 10% of the movements in Canadian variables. Furthermore, we demonstrate that all three key features are necessary to replicate the empirical evidence we documented in the VAR.

2.5.1 Estimation Method

There are two groups of parameters in the model. We calibrate the first group of parameters which are related to the steady state and commonly used in the literature. The rest of the parameters are estimated using quasi-Bayesian estimation methods.

Calibration

Table 2.3 displays our calibrated parameters. Many of these parameters are taken from previous studies. For example, we set the relative risk aversion parameter, σ, to be 2, which is standard in the business cycle literature such as Backus et al. (1994), Heathcote and Perri (2000) and Garcia-cicco et al. (2010). The capital share is set to be 0.36. The depreciation rate, δ_0, is assumed to be 0.025, which means that about 10% of capital depreciates annually.

The debt elastic interest parameter is set to a small number 0.001 to induce stationarity as in Schmitt-Grohé and Uribe (2003). Following Garcia-Cicco et al. (2010), we set υ to be 1.6, which is related to the Frisch elasticity when $\kappa = 0$.

Other calibrated parameters related to the steady states are based on the actual U.S. and Canadian data. We set the steady state growth rates of output, μ_1 and μ_2, for both the U.S. and Canada to be 0.34% per quarter using average output growth rates of the two countries between 1973Q1 and 2012Q3. In the production side, using the 2011 I-O table of the U.S., we set α_{22} to be equal to the share of the intermediate input in gross output which is 0.42. The rest of the parameters for the U.S. governing home bias for consumption and investment, ω_2^C, ω_2^I, and imported intermediate, α_{12}, are set to target the following statistics: the export share in total GDP in Canada, which is averaged to be 0.31 during the 1973Q1-2012Q3 period, consumption goods share in total export, investment goods share in total export and intermediate goods share in total export to be $0.21, 0.12$, and 0.67, respectively. These shares are calculated using the annual Canadian trade data between 1980 and 2011, and assuming the primary good is used as intermediate goods. Similarly, we set the parameters for Canada governing home bias for consumption and investment goods, ω_1^C, ω_1^I, and imported intermediate share in the production function, α_{21}, to target the followings: the average import share in total Canadian GDP to be 0.29, the consumption goods, investment goods and intermediate goods share in total import to be $0.25, 0.19$, and 0.56, respectively. In the end, the imported intermediate share in Canadian production function, α_{21}, is 0.076.

Finally, in our baseline estimation, we shut down the exogenous correlation in the technology processes for both countries by setting $\tau = 0$ and $\zeta = 0.001$, although we also estimate these parameters in the robustness section.

Quasi-Bayesian Estimation Method

In all of our estimation, we assume $\gamma_1^C = \gamma_2^C = \gamma_1^I = \gamma_2^I = \gamma_1^m = \gamma_2^m$ to keep the estimation tractable. The rest of the parameters including elasticities of substitution between home and foreign goods in both countries, investment adjustment cost, cost of utilization, wealth elasticity of labor supply and the parameters of U.S. shocks process, $\left(\gamma, s_i, \left(\frac{a_2}{a_1}\right)_i, \kappa_i, \rho_{22}, \sigma_2, \phi^D\right)$ for $i = \{1, 2\}$, are estimated by minimizing a measure of the distance between the model and empirical impulse responses. Let $IR\,(\Theta)$ denote the theoretical impulse responses given the estimated parameters Θ and calibrated parameters Θ_{-1}, and $\widehat{IR}$ is the corresponding empirical impulse responses. Since the technology process is fairly persistent and including long periods helps to identify parameters, we include the first 30 periods of each response function. To identify U.S. parameter block including its technology process and demand for Canadian goods, we include in the empirical $\widehat{IR}$ the impulse response functions of U.S. output, consumption, investment and hours. The empirical $\widehat{IR}$ also includes the responses of Canadian output, consumption, investment, hours, net export to output ratio and the terms of trade for the Canadian block. The results reported below do not change if we include real imports and real exports in $\widehat{IR}$. We find Θ to:

$$\min_{\Theta} \left[\widehat{IR} - IR\,(\Theta|\Theta_{-1})\right]' V^{-1} \left[\widehat{IR} - IR\,(\Theta|\Theta_{-1})\right] \tag{2.22}$$

Here, V is a diagonal matrix with the inverse of sample variance of $\widehat{IR}$'s along the diagonal. With this choice of V, Θ is chosen so that $IR\,(\Theta|\Theta_{-1})$ lies as much as possible within confidence interval plotted in Figure 2.2 and Figure 2.3. For practical implementation, we use quasi-Bayesian estimator proposed in Chernozhukov and Hong (2003) to estimate and construct confidence intervals for the parameters. This procedure treats the objective function above as quasi-likelihood and use Markov Chain Monte Carlo method to compute estimator.

2.5.2 Estimation Results

This section presents the main estimation results of our paper. The estimated baseline model can match over 90% of the empirical responses while without our three key features, the estimated model can explain less than 10% of the empirical responses of Canada.

The Baseline Model

We first discuss our baseline model results in terms of the estimated parameters and matching the empirical impulse responses. The first column in Table 2.4 presents the estimates of our baseline model, which includes our three key features without exogenous technology shock correlation. An important parameter in our three key features, Jaimovich-Rebelo preference parameter, κ_1, which governs the wealth elasticity of labor supply, is estimated tightly around 0.03. This estimate implies a low short run wealth elasticity of labor supply, consistent with our analysis above. Our paper is the first to provide the evidence for weak wealth effects in labor supply as previous papers in the open economy models such as Schmitt-Grohé (1998), Garcia-Cicco et al. (2010), Raffo (2009) among others often assume no wealth effects on labor supply. The second important feature of the model, the elasticity of utilization adjustment, is estimated to be small, 0.07, which means that the cost of changing utilization is low, firms can easily change the level of utilized capital. We later show that this result is consistent with how utilization data in Canada changes in response to a U.S. technology shock.

The elasticity of substitution parameter is tightly estimated to be around 0.4, implying a strong complementarity between U.S. and Canadian goods. The low value of the elasticity of substitution is consistent with the estimates in previous papers such as Corsetti et al. (2008) and Enders and Mullers (2009), which focus on the effects of U.S. productivity shocks on

U.S. real exchange rate, or Justiniano and Preston (2010) which estimate a model for the Canadian and US economyusing full information estimation. Two other parameters that we estimate are investment adjustment cost and debt elastic interest rate parameters. The investment adjustment cost is estimated to be about 5. We explore in the robustness section how much our results are driven by this adjustment cost. The debt elastic parameter affecting the interest rate that Canadian households face is quite large, 0.73, meaning a 1% change in net asset positions leads to 0.73% increase in interest rate. This estimate of the debt elastic interest rate implies that households face some financial frictions as suggested in Garcia-Cicco et al. (2010), which explains why, as we show below, this parameter matters for the large response of net exports in Canada.

In terms of model performance, our estimated model can match over 90% of the empirical responses of Canadian economy observed in the data, on average[11]. We plot in Figure 2.5 the theoretical responses of Canadian variables in response to a positive U.S. permanent technology shock occurred in period one calculated at the mean of the posterior draws, together with the empirical responses from the VAR. Consistent with the data, in response to a positive U.S. permanent technology shock, Canadian output, consumption, investment and hours increase and the terms of trade appreciate. In particular, the model can capture the gradual boom in Canadian economy, which is due to the extremely slow diffusion technology process and a substantial transmission through international trade As τ is set to be zero and ζ is close to zero, technology in Canada does not increase. Instead, given the gradual increase in U.S. economic activities, the strong endogenous transmission mechanism within the model enables us to replicate the substantial increase in both hours and output in Canada in the short run within five to ten quarters. Consistent with our analysis, when there is a positive

[11]Specifically, for each point, we compute the absolute distance between the empirical and theoretical impulse responses divided by the empirical impulse responses and take average.

U.S. permanent technology shock, U.S. goods are more abundant, causing Canadian terms of trade to appreciate. As a result, even though technology in Canada does not increase, the strong increase in labor demand in Canada and a weak wealth effects on the labor supply lead to a substantial increase in hours in equilibrium. Since hours increase, output in Canada can increase. Investment also increases because of the complementarity between hours and capital. In the end, the model can account for over 90% of the movements of macroeconomic activities in Canada, in contrast with the negative results in previous studies such as Schmitt-Grohé (1998) and Justiniano and Preston (2010) to explain the transmission of US shocks across countries. This result demonstrates that international real business cycle models with our three key features changing both the production side and household preferences can generate substantial transmission through international trade, consistent with the empirical evidence.

The natural question is, then, if our estimated three key features are consistent with the data. To that end, we plot in Figure 2.6 the dynamic responses of Canadian capacity utilization, real wages to a positive U.S. permanent technology shock implied by the model alongside with their empirical counterparts. First, the estimated model matches the empirical responses of real wage in Canada to U.S. permanent technology shocks in the short run. We measure real wages as total wage and compensation deflated by CPI between 1981Q1 and 2012Q3. The reason we pay attention to real wage is that real wage is informative about the relative role of labor supply and demand. For example, if there is a large negative wealth effect on labor supply, and labor demand shifts sufficiently to increase hours in equilibrium, we should observe a large increase in real wage. On the other hand, if the labor supply curve is flat and the wealth effect is small, and the demand curve shifts to increase hours, we should observe a small increase in real wage. Empirically, real wage does not move much in the short run and increases significantly in the long run, which is consistent with our results as in our estimated model in the short run, the shift in labor demand dominates and real wage does not increase substantially. In terms of magnitude, the real wage movements in our model are smaller than the large increase in real wage after five quarters. Nevertheless, this evidence suggests that the low wealth effect on labor supply feature of our estimated model is consistent with the data in the short run.

Second, our estimated model also does not overpredict the role of capacity utilization. To see this, we plot the theoretical impulse responses of capacity utilization together with its empirical counterparts, constructed from a measure of capital utilization from the Canadian Statistics and Bank of Canada between 1973Q1 and 2012Q3. There is a clear consistency in direction between the model and the data even though the model implies a smaller response of capacity utilization. As variable capacity utilization is one of the key features of our model, this result, if anything, indicates that we understate the importance of variable capacity utilization.

To further assess the performance of the model, we examine the responses of real exports and real imports implied by the model against their empirical counterparts. As plotted in Figure 2.6, the model correctly predicts that both real exports and real imports increase after a U.S. permanent technology shock. The magnitudes of both real exports and real imports are slightly lower than the empirical counterparts. A possible reason for a smaller increase in real exports is that our model abstracts from vertical production sharing, which differs from imported intermediate input in the sense that some Canadian exports which include imports from the U.S. are only consumed in the U.S.. When a good U.S. shock happens, the volume of trade are magnified with the vertical production sharing, so the responses of gross real exports can be larger than our baseline model. Nevertheless, imported intermediate inputs help the model to generate substantial increase in both exports and imports, consistent with the data[12].

The estimation results demonstrate that our model is capable of generating substantial transmission through international trade. Furthermore, we document additional evidence which suggests that our mechanism is consistent with the observed behaviors of the data in Canada.

The Model Without our Three Key Features

To show that our three key features are central to endogenous transmission through international trade, we show that the estimated model without our three key features cannot generate substantial endogenous transmission and fails to account for the responses of Canadian economy observed in the data. To that end, we modify the baseline model as follows: household preferences are the standard King-Plosser-Rebelo preferences by setting $\kappa_1 = 1$, there is no variable capacity utilization, and there is no imported intermediate input. We re-estimate this model using the same method as in the baseline model. The number of parameters estimated in this case is two parameters fewer than the baseline model: Jaimovich-Rebelo parameter κ_1 and utilization cost $\left(\frac{a_2}{a_1}\right)_1$.

The estimated parameters along with its confidence intervals are displayed in Column 3 of Table 2.4. Compared to the baseline model, the elasticity of substitution is larger, 0.79, but is still smaller than one, suggesting that U.S. and Canadian goods are complements. The other parameters, investment adjustment cost and debt elastic parameter, are much different

[12] We also examine the movement of real interest rate in Canada, which is a possible mechanism through which the model generates endogenous transmission. For example, Hernandez and Leblebicioglu (2012) highlight the change in interest rate though working capital channel amplifies the effects of U.S. shocks to Mexico. However, we find that in the context of Canada and the U.S., conditional on permanent technology shocks, the movement of real interest rate is very small, casting doubt on the role of interest rate in generating endogenous transmission. In fact, when we add working capital requirement for wage payment as in Neumeyer and Perri (2005), endogenous transmission generated by working capital is negligible and the performance of the model is quantitatively similar to our baseline model.

from those estimated in the baseline model, although we show later that these features do not affect our results.

To assess the performance of the model, we plot in Figure 2.7 the impulse responses implied by this estimated model along with the empirical responses of the macroeconomic variables in Canada. Clearly, the model without our three key features is unable to capture the dynamic responses of output and hours as well as other aspects of the data such as consumption and investment. In fact, only about 10% of the Canadian responses observed in the data can be accounted for by this model. Although the model predicts a gradual increase in Canadian economic activities because of the small cointegrating technology process, the magnitude of the increase is much smaller than observed in the data. Since the model tries to match not only output, hours, consumption but also the terms of trade, the estimated model overpredicts the magnitude of the appreciation of the terms of trade in order to have hours to increase. Nevertheless, with the strong wealth effect as the model tries to match consumption behavior, hours decrease on impact and increase only slightly in the longer run, consistent with our analysis above. Without much change in hours, output in Canada cannot increase. In other words, without our three key features, the model cannot generate substantial endogenous transmission.

2.6 Understanding the Features of the Model Quantitatively

This section analyzes quantitatively the key features of the baseline model which can help the model to generate substantial endogenous transmission. More specifically, we show that *all* three key features in the model interacting with each other are necessary for the model's success. Furthermore, other features often used in the open economy literature such as investment adjustment cost and debt elastic interest rate are not essential to the model's success.

2.6.1 The Three Key Features

We first estimate variants of the baseline model where we keep only one of the three key features with a maintained assumption that there is no exogenous technological spillover, and find that these models cannot quantitatively generate sufficient endogenous transmission. More specifically, we plot in Figure 2.8 the three variants of the baseline model: (i) with only Jaimovich-Rebelo preferences and without variable capital utilization and imported intermediate inputs, "JR", (ii) with only variable capacity utilization and without Jaimovich-Rebelo preferences and imported intermediate inputs, "utilization", and (iii) with only imported intermediate inputs and without variable capital utilization and Jaimovich-Rebelo preferences, "intermediate". To see how keeping one feature helps to generate endogenous transmission compared to standard models , we also plot in the same figure the case when there is none of the three frictions, "w/o all three". None of the variants can generate the substantial increase in output and hours in Canada although these models do a better job at matching consumption and investment. In the case with only Jaimovich-Rebelo preferences, we find that the estimated wealth effect is close to zero. However, consistent with our intuition above, even in the absence of wealth effect, the movements of the terms of trade are too small to generate a substantial increase in hours. As a result, the "JR" variant of the baseline model exaggerates the appreciation of the terms of trade but still falls short in explaining the movement of hours and output in Canada. Similarly, both the model with only variable capacity utilization and the model with only imported intermediate inputs also fall short in explaining the movements of output and hours in Canada while trying to match the terms of trade and other variables. Overall, these variants of the baseline model do not improve the match of the baseline model without three key features, “w/o all three”.

We explain the intuition for the results above as follows. The estimation tries to fit not only hours and output in Canada but also the terms of trade and consumption. These models can match the movements of output and hours if the terms of trade appreciate more. Therefore, the terms of trade are predicted to appreciate more than observed in the data in all cases. Nevertheless, since the estimation procedure also tries to fit the terms of trade, this appreciation cannot be large enough to fit output and hours. Moreover, without Jaimovich-Rebelo preferences, the estimation faces a trade off between an increase of consumption and hours. If the model fits an increase of consumption, it implies a large negative wealth effect on labor supply, leading to a smaller increase in hours. Therefore, the estimation tends to underpredict the increase of consumption to generate a larger increase in hours. On top of these problems, investment is underpredicted in the case “utilization”, i.e. the standard model with only variable capital utilization. One reason is that the return to investment, which is related with the expected marginal product of capital, does not increase sufficiently in the model since hours do not increase sufficiently. If hours increase more, marginal product of capital can increase and so can investment. In other words, the match of investment is related with the match of hours. Additionally, in all cases, the model cannot account for the large increase in Canadian net export over output ratio. The intuition for this result is the fact that output does not increase much to give an incentive for households to save more. Therefore, this problem is also related with the problem of hours.

Another way of showing how our three key features are crucial in generating substantial endogenous transmission is to look at the behavior of the baseline model with two features only. We plot in Figure 2.9 the three cases when one of the features is shut down from the estimated baseline model, keeping other estimated parameters. When we shut down Jaimovich-Rebelo preferences, the model predicts much smaller responses of the output and hours. As explained above, this is because of the strong wealth effect associated with King-Plosser-Rebelo preferences. Without variable capital utilization, the model actually predict larger movements of output and hours than the data. However, the reason for such large change in hours is that the model also predicts too large an appreciation of the terms of trade. Lastly, without imported intermediate goods inputs, the model also cannot match the large movements of output and hours, consistent with the role of imported intermediate goods discussed above.

These exercises demonstrate that all of three key features are important for the model to generate substantial endogenous transmission, which comes from the movements of hours. More generally, we argue that we need to consider features that affect the labor demand and supply conditions to be able to generate strong endogenous transmission. For the labor supply side, we need features that prevent labor supply to decrease sharply. It can be other features such as real wage rigidity, in which households need to supply labor given a fixed real wage. For the labor demand side, we need frictions which increase demand sufficiently. It can also be time varying countercyclical markup such as deep habit mechanism. Judging the relative importance of those frictions requires additional data and is beyond the scope of this paper. We argue that between Canada and the U.S. our features are sufficient to explain the observed transmission of U.S. permanent technology shocks, and are supported by both empirical and theoretical grounds.

2.6.2 Other Features

Our baseline model also departs from the plain vanilla international business cycle models by having investment adjustment cost, which is often used in the literature such as Christiano et al. (2005), or the debt elastic interest rate in the small open economy literature such as Garcia-cicco et al. (2010). We show that the model's ability to generate substantial endogenous transmission does not depend on these two features.

Since investment adjustment cost is estimated to be large in the baseline model, we examine how shutting down this investment adjustment cost affects our results to examine its role in generating substantial endogenous transmission. To that end, we estimate a version of the baseline model where there is no investment adjustment cost, i.e. $s_1 = 0$. The theoretical responses of the estimated model are plotted in Figure 2.10. We find that investment still increases, so do consumption and output. Other responses also match up to 90% of the empirical impulse responses. In other words, the role of investment adjustment cost is negligible in generating endogenous transmission. Investment adjustment cost reduces the volatility of investment, but does not stop the outflow of investment from Canada to the U.S.. The reason for the right response of investment is the increase in hours. With the three key features in the model, hours can increase, causing marginal product of capital to increase, leading to an increase in investment. In the baseline model, when we set $s_1 = 0$, i.e. there is no investment adjustment cost, investment would increase too large relatively to the data so the estimated utilization cost turns out to be larger than the baseline model.

Second, although our baseline model estimates the debt elastic parameter, ϕ_D to be large, this result is not crucial for the model to generate substantial movements of output and hours in Canada. In our model, the debt elastic interest rate reflects the financial friction that households face in international borrowing and lending. Our baseline model estimates that this debt elastic parameter, ϕ_D, is large, implying that there is a high cost of borrowing or lending internationally for Canadian households. Nevertheless, this parameter turns out to be not important in explaining the observed responses of output and hours in Canada. When we re-estimate the model with ϕ_D being set to be small, 0.001, as plotted Figure 2.10, this version of the baseline model can still match most of the empirical impulse responses of Canada. The exception is the net exports in Canada, which is lower than the empirical response. Therefore, we conclude that ϕ_D is not important to generate endogenous transmission in the model but has a role in explaining the movement of net exports.

Finally, although not shown here, the model with neither investment adjustment cost nor high debt elastic interest rate can still match the effects of U.S. permanent technology shocks on Canada. In other words, the success of our model only depends on the three key features which directly affect the responsiveness of the labor market to changes in international relative prices.

2.7 Robustness

Since the observed boom in Canada after a positive U.S. technology shock may be due to an exogenous correlation of technology shocks between the U.S. and Canada, we let the data speak by estimating a version of the baseline model where the exogenous correlation of technology, "baseline with correlation," is estimated. The estimated parameters of this version of the baseline model are presented in the second column in Table 2.4. Notice that the estimated parameters of this model are similar to those of the baseline model. In fact, the estimated direct technology correlation τ is 0.10, but its 90% confidence interval includes zero, which means that the shocks are not strongly correlated. Moreover, the cointegration parameter, ζ, is estimated to be close to 0.

As the estimated parameters are similar between the baseline model with correlation and the baseline model, the estimated baseline model with exogenous correlation of technology shocks matches the empirical responses similar to the baseline model estimated without exogenous correlation, as plotted in Figure 2.11. In particular, the baseline model with correlation can also replicate the gradual responses of the Canadian economy, and on average match over 90% of the empirical responses. Shutting down exogenous correlation of technology while keeping the other estimated parameters, we find that the match of the model does not deteriorate. This result suggests that the data assign a negligible role to the exogenous correlation of technology shocks and a larger role for the endogenous transmission, which is consistent with the empirical evidence in the VAR presented above.

Finally, to further illustrate that exogenous correlation of technology shocks cannot help the model without our three key features to match the data, we re-estimate the model without our three key features allowing for exogenously correlated technology shock. As shown in the last column of Table 2.4, the estimated parameter for the cointegrating process, ζ, is 0.92 and that for the contemporaneous correlation of shock, τ, is 0.75, both of which are large and significant. In other words, the estimation prefers exogenous correlation in order to explain the large responses of output. However, as shown in Figure 2.12, even though the strong exogenous correlation of technology shocks helps output in Canada to increase, the responses of hours are still much smaller than the empirical counterpart. This result demonstrates two points. First, when the model is not able to generate substantial endogenous transmission, the estimation requires a strong exogenous correlation of technology shocks in order to replicate the data. Second, exogenous correlation by itself is not a panacea to comovement pattern in the data if we take into account not only output but also hours and the terms of trade.

2.8 Extension: Model with Nominal Rigidities

We now show that our three key features also help international business cycle models with nominal rigidities, or the New Open Economy Macroeconomic (NOEM) models to generate substantial transmission through international trade. More specifically, we discuss how NOEM models can potentially generate transmission through international trade but fail when confronted with the data. Once we add our three key features into international business cycle models with nominal rigidities, we can explain the data.

To that end, we introduce nominal rigidities in the form of sticky price into our baseline model. To simplify our exposition, we only explain the structure of country 1 that is different from the baseline model. Country 2 is simply the closed economy version of country 1. The final good producers combine a continuum of intermediate goods $Y_{1t}(j)$ where $j \in [0,1]$ to produce final good Y_{1t} using the following technology:

$$Y_{1t} = \left[\int_0^1 Y_{1t}(j)^{\frac{1}{\eta_p}} dj \right]^{\eta_p}, \tag{2.23}$$

where η_p is the price markup in the steady state. The intermediate good producers are monopolistic firms who produce differentiated intermediate goods $Y_{1t}(j)$ using the production function of the following form:

$$Y_{1t}(j) \leq \left(u_{1t}(j) K_{1t}(j)\right)^{\alpha} \left(Z_{1t} H_{1t}(j)\right)^{1-\alpha} - FC_{1t}, \tag{2.24}$$

where FC_{1t} is the fixed cost included to have zero profits in the steady state. We assume that the intermediate goods firms can change the price with a fixed probability θ_{1p} as in Calvo (1983) in every period. Lastly, we assume that monetary policy is conducted according to the Taylor-type rule of the form:

$$\ln R_t^D = \rho_R \ln R_{t-1}^D + (1-\rho_R) \left[\ln R_{ss}^D + s_{\pi} \ln \left(\frac{\pi_{1t}}{\pi_1^*} \right) + s_{\Delta Y} \ln \left(\frac{\Delta Y_{1t}}{\Delta Y_{1ss}} \right) \right], \tag{2.25}$$

where R_{ss}^D is the steady state level of nominal interest rate, π_1^* is the steady state level of inflation and ΔY_{1t} is the growth rate of output and ΔY_{1ss} is the steady state level of ΔY_{1t}.

In theory, without our three key features, NOEM models can generate endogenous transmission. To see this, we look at the labor supply and labor demand conditions:

$$MRS_{1t} = W_{1t} \text{ and } W_{1t} = \frac{1}{\mu_t^p}\frac{\partial F}{\partial H_{1t}} p_t^D,$$

where μ_t^p is the price markup in country 1. Compared to the standard international real business cycle models without our three key features, this model has the price markup term appearing in the labor demand condition. Therefore, even though in response to a U.S. technology shocks, with a positive wealth effect, labor supply decreases in Canada, hours worked in Canada can still increase if the price markup decreases substantially, implying that the movements of markup are crucial for this mechanism to work.

To understand how much markup can help standard NOEM models without our three key features to generate endogenous transmission, we examine how Canadian markup responds to a U.S. technology shocks. To that end, we document the responses of inflation in Canada. The reason to use inflation is that the Phillips curve, given by

$$\pi_{1t} = \beta E_t \pi_{1t+1} - \lambda_p \mu_t^p, \tag{2.26}$$

where π_{1t} is the inflation rate of country 1 at time t, dictates the relationship between the price markup and inflation. In other words, one can look at how inflation in Canada responds to a U.S. technology shock to infer the strength of the markup channel to generate endogenous transmission. Therefore, we augment the baseline VAR specification with inflation and nominal interest rate in both the U.S. and Canada. We plot the responses of Canadian inflation as well as other variables in Figure 2.13. Compared to the baseline VAR, this VAR specification augmented with inflation and interest rate does not alter the direction or the relative magnitude of the responses in Canadian economy. The main result of this extended VAR is that the responses of inflation are almost zero, suggesting that it is unlikely that markup would move enough to generate substantial transmission as observed in the data.

We validate our intuition that the movements of markup are not enough to help standard NOEM models to reconcile with the data by estimating our NOEM model above without the three key features. More specifically, we match additionally the theoretical impulse responses of Canadian inflation and interest rate with their empirical counterparts to estimate the parameters of the model including the sticky price parameter. The estimation shows that the data prefer a specification with an unreasonably high price rigidity, i.e. estimated θ_{1p} is about 0.99. The reason is that the estimation tries to match the movements of both inflation and hours. Since the model requires a substantial decrease in markup to explain a large response of hours and inflation decreases slightly in the data, the estimation would choose prices to be fixed so that markup can move freely. Therefore, when we restrain the price rigidities, $\theta_{1p} \leq 0.75$, we find hat the NOEM model without our three key features fails to match the substantial movements of hours and output in Canada and exaggerating the movements of the terms of trade, as displayed in Figure 2.14.

Finally, we estimate the NOEM model with our three key features to show that our mechanism still holds in this case. As plotted in Figure 2.14, the NOEM model with the three key features can match the data reasonably with estimated nominal price stickiness $\theta_p = 0.71$. In particular, the model is able to come close to matching the movements of hours in Canada, replicate very well the responses of Canadian output while matching the inflation movements reasonably well. This result highlights the importance of our features to match the transmission observed in the data.

The final exercise in our extension is to add nominal wage rigidities in the form of sticky wage into the model. In this case, we also find that our baseline model with both nominal price and wage rigidities can match the data reasonably with estimated price and wage stickiness to be around 0.68 and 0.38. Once we shut down our three key features, this model would require wage stickiness to be 0.99. Again, this result suggests that our features are important to match the transmission observed in the data.

Related to the Literature Our extension exercises relate our work with existing work in the NOEM literature. In particular, we compare our result with Justiniano and Preston (2010), who estimate a standard NOEM model without capital accumulation using U.S. and Canadian data and fail to explain the strong transmission of U.S. shocks to Canada. Although they use full information estimation method and consider overall comovement rather than conditional comovement, our analysis shed light on why they have a negative result that U.S. shocks in their estimated model cannot explain Canadian business cycles, in contrast with the data. Among other possible problems, we find that their lack of the three key features that we propose makes it hard to generate substantial endogenous transmission of shocks from the U.S. to Canada. More specifically, they use a standard preference with a substantial wealth effect, decreases labor supply, and without variable capital utilization and imported intermediate inputs, there is no strong reason for labor demand to increase. Although their NOEM model includes nominal rigidities in the form of sticky price and wage but as we argue above, markup movements associated with these frictions do not necessarily generate large endogenous transmission when trying to match with the data such as the dynamic of inflation and real wage. Therefore, it is possible that their model cannot explain strong comovement between these two countries.

2.9 Conclusion

This paper examines the transmission mechanism of technology shocks across countries. We show that the nature of such transmission depends fundamentally on the features that determine the responsiveness of labor supply and labor demand to international relative price. We augment a standard real international business cycle model with three key features that can generate substantial endogenous transmission. The three key features are a preference specification which controls for the wealth elasticity of labor supply, variable capacity utilization and imported intermediate inputs. Estimating this model using the data for Canada and the U.S. between 1973Q1 and 2012Q3, we show that it can explain over 90% of the observed effects of permanent U.S. technology shocks on Canadian output and hours. We find that endogenous transmission explains the majority of the observed comovement conditional on permanent U.S. technology shocks while exogenous correlation of technology shocks is not important. Our estimation further suggests that we need all three key features for the success of the model in replicating the data. We extend the model to include nominal rigidities and show that our insights also carry over to this setting.

Despite our initial success on matching conditional comvement, much work can be done in the international business cycle area. An interesting application of our mechanism is to use the proposed model to resolve the trade-comovement puzzle documented in Kose et al. (2006), as we suggest that our mechanism generates substantial comovement through international trade alone. Another extension of this paper is to investigate if there is any different transmission mechanism of other foreign shocks such as government spending or oil price shocks. Finally, future work can focus on the ability of the model to quantitatively account for the overall comovements across countries taking into account the movements of international relative prices such as the terms of trade.

2.10 Tables and Figures

	2 quarters ahead	4 quarters ahead	8 quarters ahead	20 quarters ahead
Output	0.12	0.23	0.39	0.52
Consumption	0.08	0.16	0.26	0.35
Investment	0.04	0.07	0.08	0.14
Hours	0.05	0.15	0.24	0.34
Net exports to output	0.04	0.07	0.23	0.4
Terms of trade	0.03	0.08	0.14	0.19
Real exports	0.18	0.27	0.48	0.57
Real imports	0.11	0.23	0.34	0.42

Table 2.1: Forecast variance decomposition of Canadian variables conditional on the U.S. permanent technology shock

Number of vectors	Eigenvalue	Trace	5% critical value	Max-Eigenvalue	5% critical value
0		5.72	15.41	5.43	14.07
1	0.1	0.28	3.76	0.28	3.76

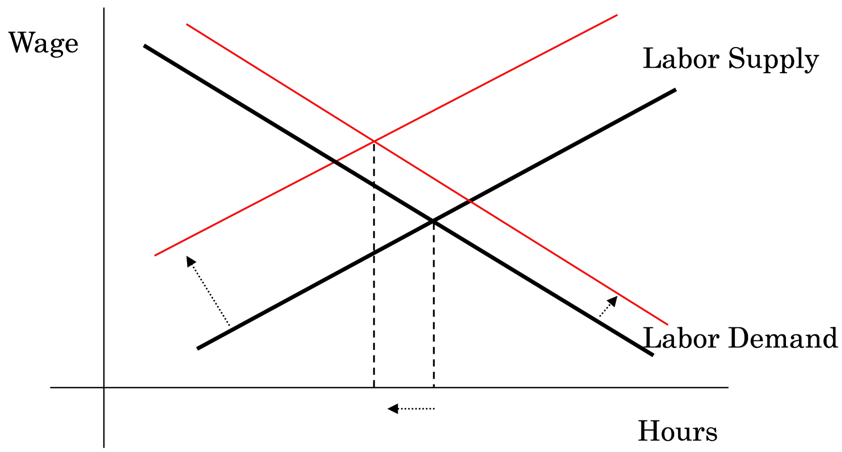
Table 2.2: Cointegration statistics: Johansen's test for output

	Parameter	Value	References
β	discount parameter	0.99	
σ	risk aversion	2	Heathcote and Perri (2002)
v	governing Frisch elasticity	1.6	Garcia-Cicco et. al. (2010)
α	capital share	0.36	Backus et. al. (1992)
δ	depreciation rate of capital	0.025	Backus et. al. (1992)
μ_1	steady state output growth in Canada	1.0034	average Canadian data
μ_2	steady state output growth in the U.S.	1.0034	average U.S. data
α_{11}	Canadian intermediate share	0.45	Canadian I-O table 2009
α_{21}	Canadian imported intermediate share	0.076	Canadian I-O table 2009
α_{22}	U.S. intermediate share	0.42	U.S. I-O table 2011
ω_1^C	consumption home bias	0.90	target $\frac{F_1^C}{RIMP} = 0.25$
ω_1^I	investment home bias	0.77	target $\frac{F_1^I}{RIMP} = 0.19$

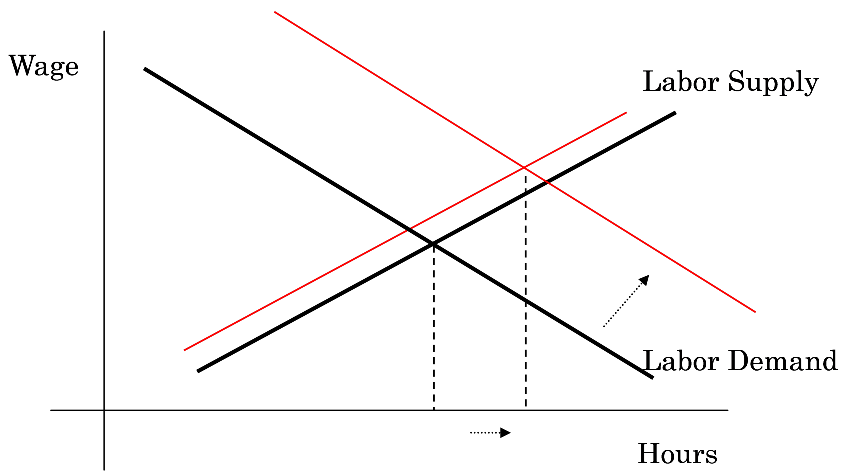
Table 2.3: Calibrated parameters

	Parameter	Baseline	Baseline w/ correlation	W/o 3 key features	W/o 3 key features w/ correlation
		Canada block			
γ	Elasticity of substitution	0.40	0.39	0.79	0.65
		(0.36,0.44)	(0.35,0.44)	(0.75,0.83)	(0.62,0.69)
s_1	Investment adjustment cost	5.07	5.08	1.37	8.00
		(1.32,9.08)	(1.24,9.07)	(0.19,4.18)	(5.15,9.79)
κ_1	Jaimovich-Rebelo parameter	0.03	0.04		
		(0.03,0.04)	(0.03,0.05)		
$(a_1/a_2)_1$	Utilization cost elasticity	0.07	0.08		
		(0.02,0.15)	(0.02,0.17)		
ϕ_D	debt elastic	0.73	0.75	0.03	0.00
		(0.41,0.97)	(0.47,0.97)	(0.00,0.10)	(0.00,0.01)
		Shock processes			
ρ_2	Autoregressive for U.S. technology	0.79	0.79	0.77	0.71
		(0.75,0.82)	(0.76,0.83)	(0.73,0.80)	(0.67,0.75)
σ_2	Standard deviation of U.S. shock	0.17	0.16	0.17	0.21
		(0.14,0.20)	(0.14,0.19)	(0.15,0.21)	(0.19,0.24)
τ	Direct technology correlation		0.10		0.75
			(-0.18,0.37)		(0.51,0.94)
ζ	Cointegration parameter		0.00		0.92
			(0.00,0.01)		(0.80,0.99)
		U.S. block			
s_2	Investment adjustment cost	2.24	2.06	8.04	1.34
		(0.84,4.33)	(0.71,3.91)	(5.49,9.77)	(0.11,3.32)
κ_2	Jaimovich-Rebelo parameter	0.03	0.03	0.02	0.02
		(0.02,0.04)	(0.02,0.03)	(0.02,0.03)	(0.02,0.03)
$(a_1/a_2)_2$	Utilization elasticity	0.12	0.11	0.09	0.27
		(0.02,0.27)	(0.02,0.24)	(0.02,0.21)	(0.16,0.40)

Table 2.4: Estimated parameters for the baseline model with and without correlation of technology shocks, for the simplified model with and without correlation of technology shocks. The numbers in parentheses are the $5-95\%$ confidence intervals calculated from the quasi-Bayesian estimation.



(a) Plain vanilla case



(b) With three key features

Figure 2.1: Intuition for why model generates endogenous transmission

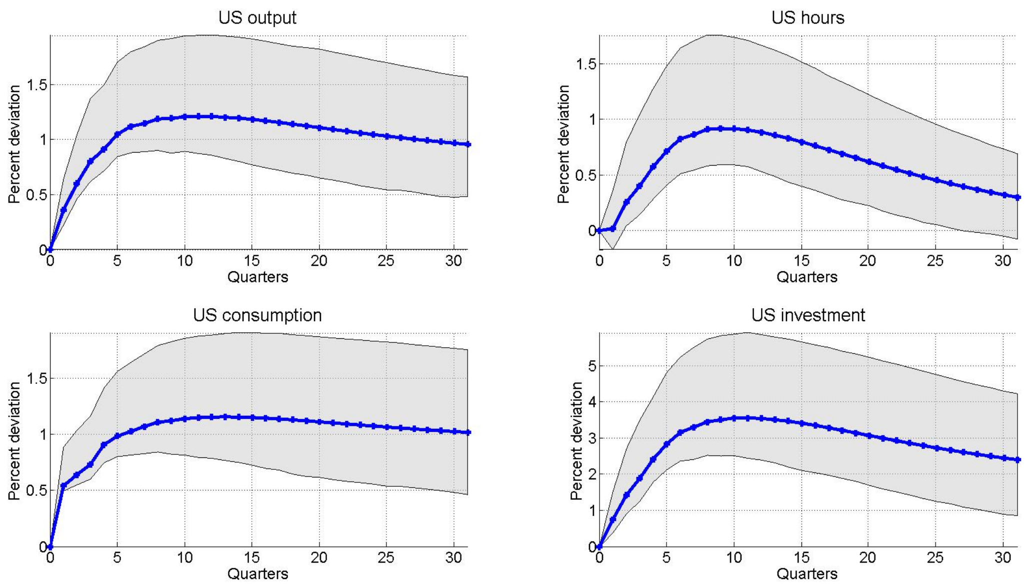


Figure 2.2: Responses of the U.S. output, consumption, investment and hours to the U.S. technology shock occurring in period one. Lines with plus sign is the point estimate and the shaded areas are the 95% confidence intervals.

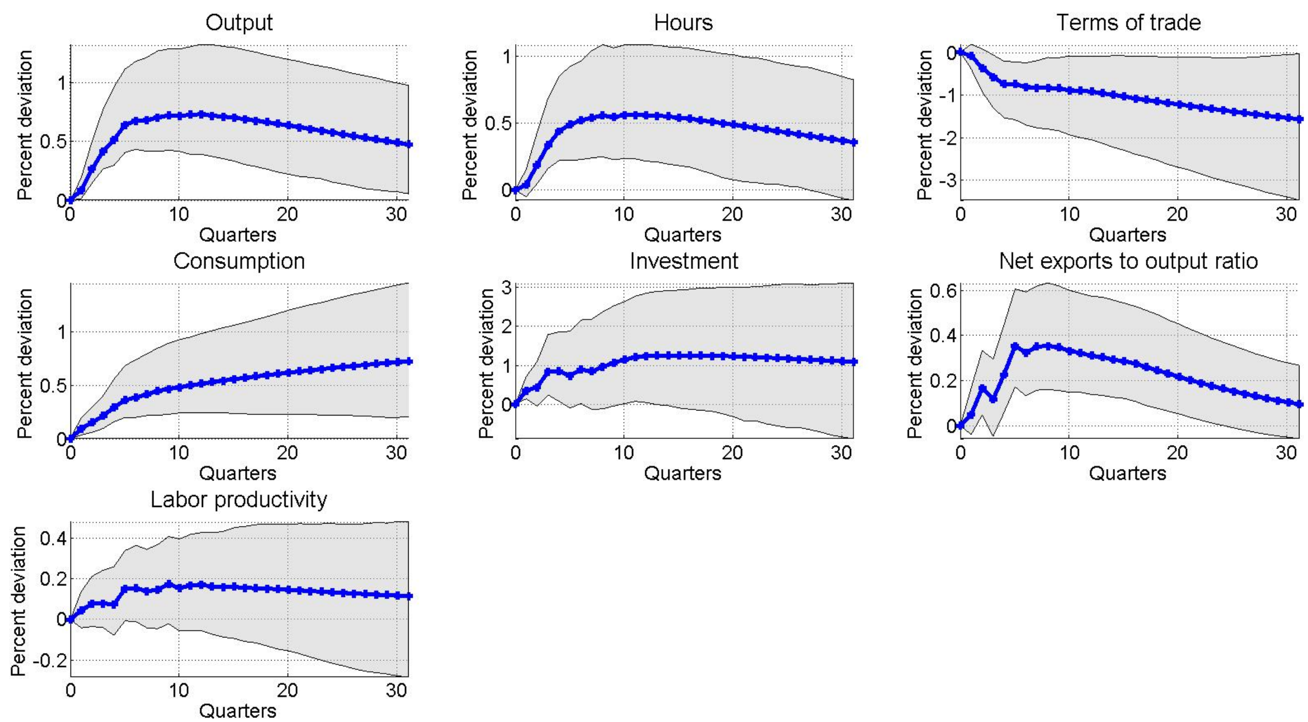


Figure 2.3: Canadian output, consumption, investment, hours, terms of trade, net export, labor productivity to a positive U.S. technology shock occurring in period one. Lines with plus sign is the point estimate and the shaded areas are the 95% *confidence intervals.*

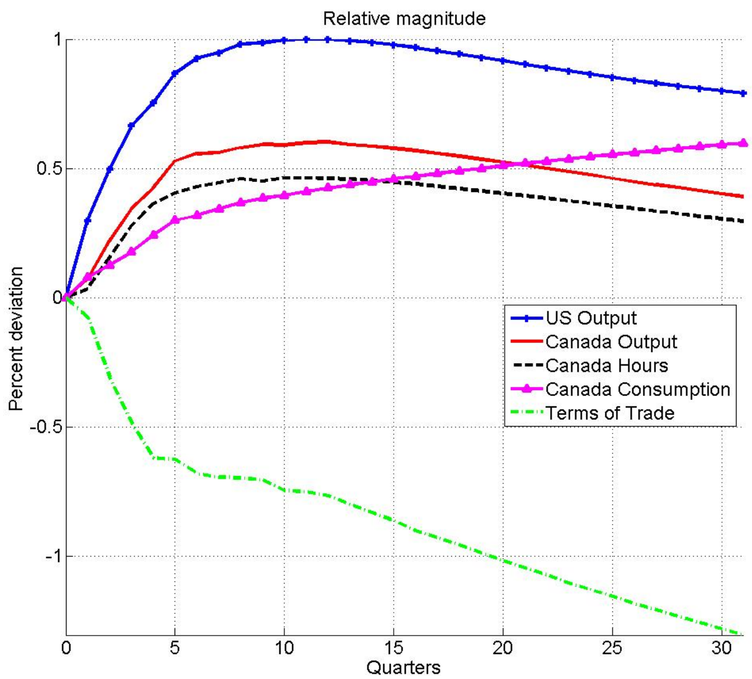


Figure 2.4: Relative magnitude of the responses of Canadian economy to the U.S.

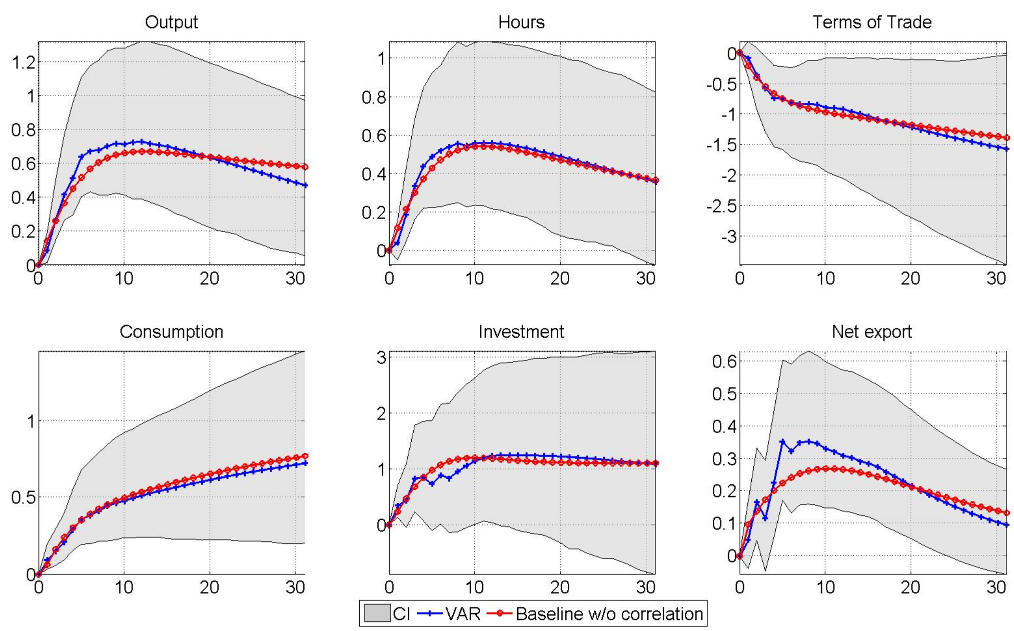


Figure 2.5: The theoretical impulse responses of Canadian economy to a positive U.S. shock. Lines with plus sign is the point estimate and the shaded areas are the 95% *confidence intervals. Lines with square sign is theoretical responses of the baseline model.*

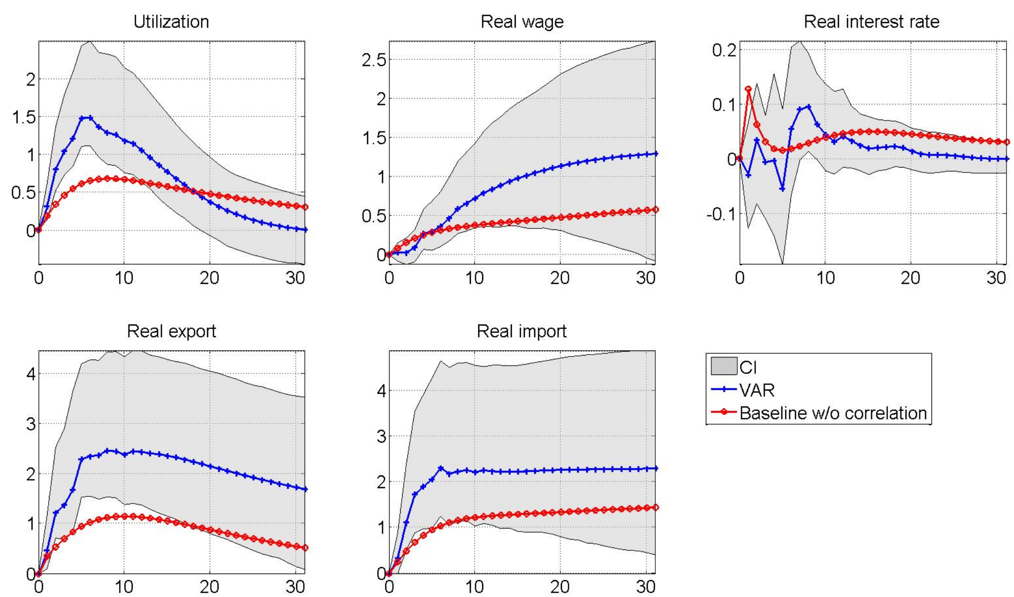


Figure 2.6: The theoretical impulse responses of additional variables for Canadian economy to a positive U.S. shock. Lines with plus sign is the point estimate and the shaded areas are the 95% *confidence intervals. Lines with square sign is theoretical responses of the baseline model.*

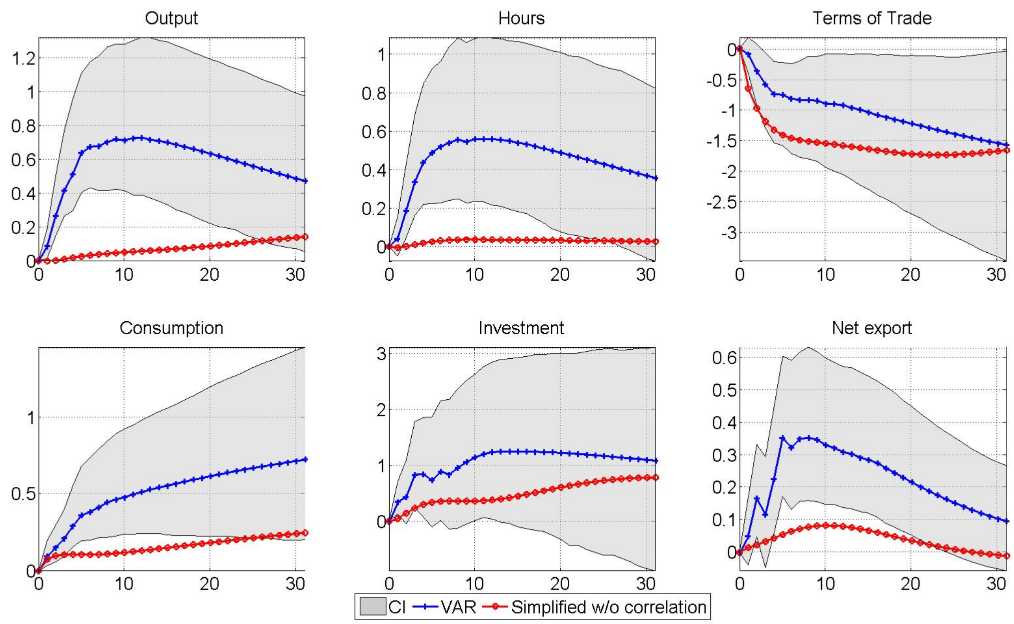


Figure 2.7: The theoretical impulse responses of Canadian economy to a positive U.S. shock in the baseline model without our three key features. Lines with plus sign is the point estimate and the shaded areas are the 95% *confidence intervals. Lines with squared sign is the theoretical responses from the baseline model without our three key features.*

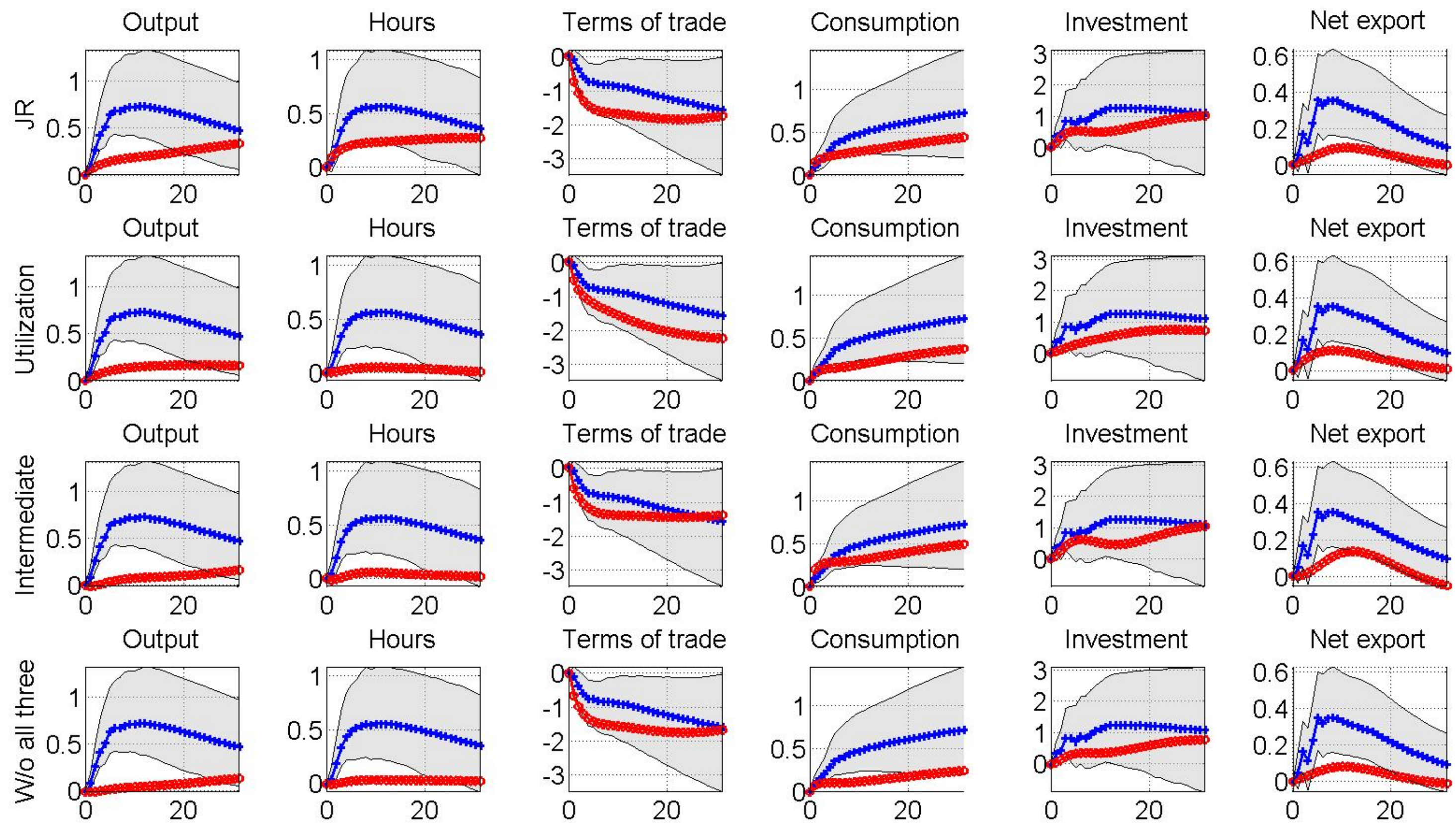


Figure 2.8: The importance of our features in generating endogenous transmission: The estimated variants of the baseline model when there is only one feature. Lines with plus sign is the point estimate and the shaded areas are the 95% *confidence intervals. Lines with squared sign is theoretical responses from the model listed on the y-axis, where (i) the baseline model without variable capital utilization and imported intermediate inputs, "JR", (ii) the baseline model without variable capital utilization and Jaimovich-Rebelo preferences, "intermediate", (iii) the baseline model without Jaimovich-Rebelo preferences and imported intermediate inputs, "utilization", (iv) the baseline model without any of the three frictions, "w/o all three".*

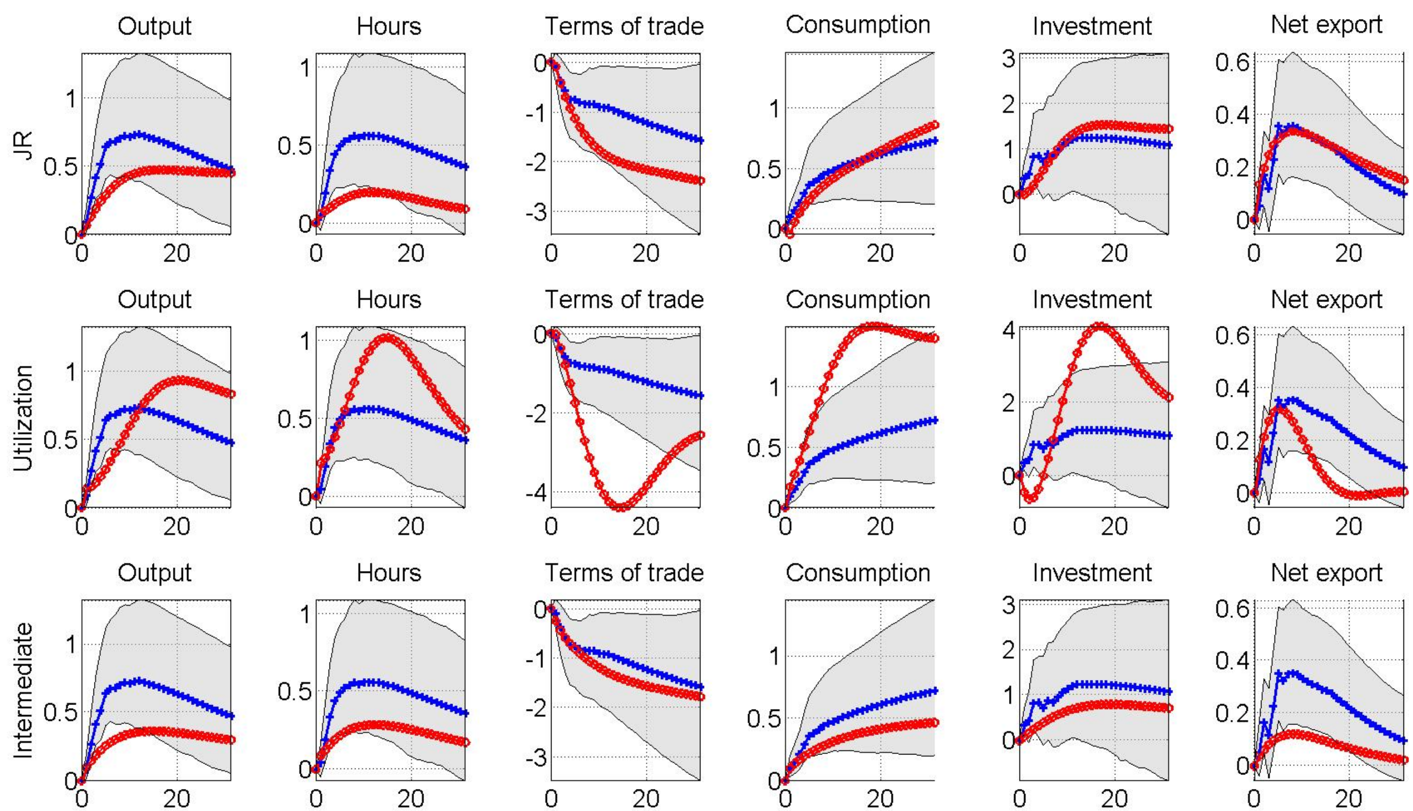


Figure 2.9: The importance of our features in generating endogenous transmission: Using the baseline estimated parameters, the responses of the model when one feature is shut down. Lines with plus sign is the point estimate and the shaded areas are the 95% confidence intervals. Lines with squared sign is theoretical responses from the model listed on the y-axis.

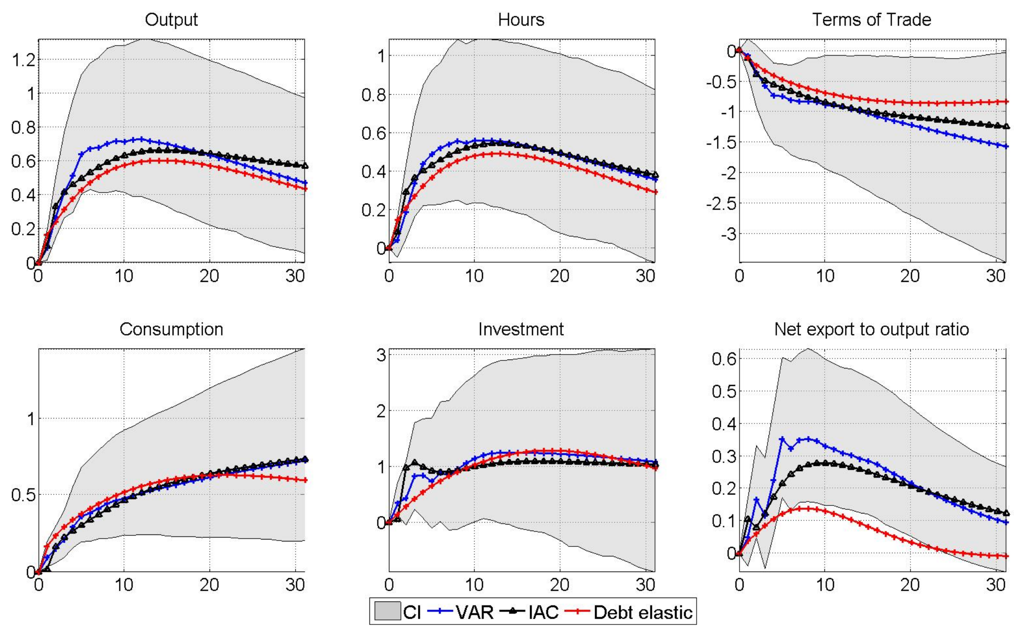


Figure 2.10: Robustness of the results when the baseline model has no investment adjustment cost, debt elastic interest rate. Lines with plus sign is the point estimate and the shaded areas are the 95% confidence intervals.

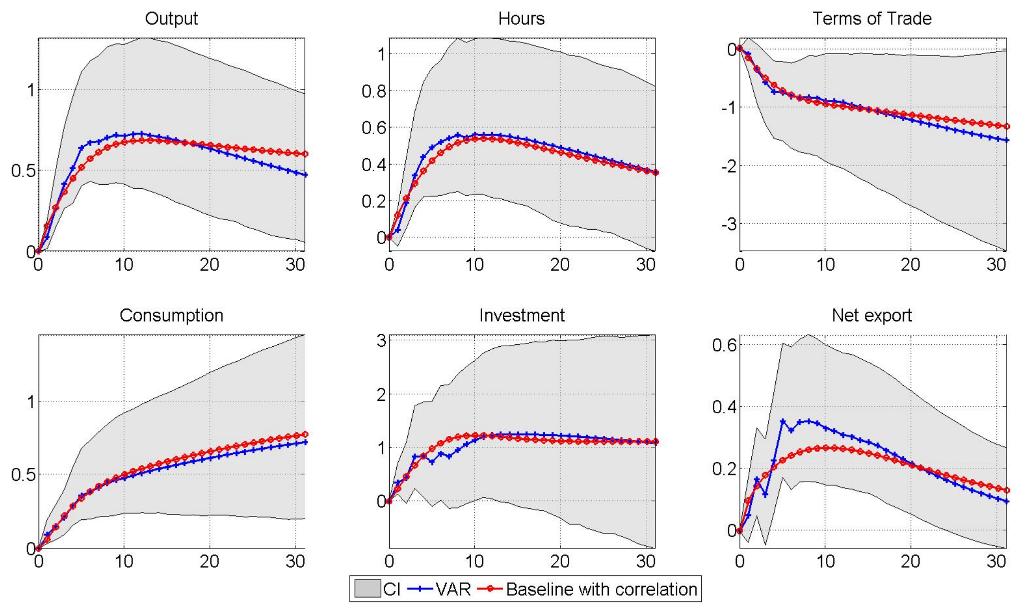


Figure 2.11: The theoretical impulse responses of the baseline model with exogenous correlation of technology shocks to a positive U.S. shocks. Lines with plus sign is the point estimate and the shaded areas are the 95% confidence intervals. Lines with squared sign is theoretical responses from baseline model.

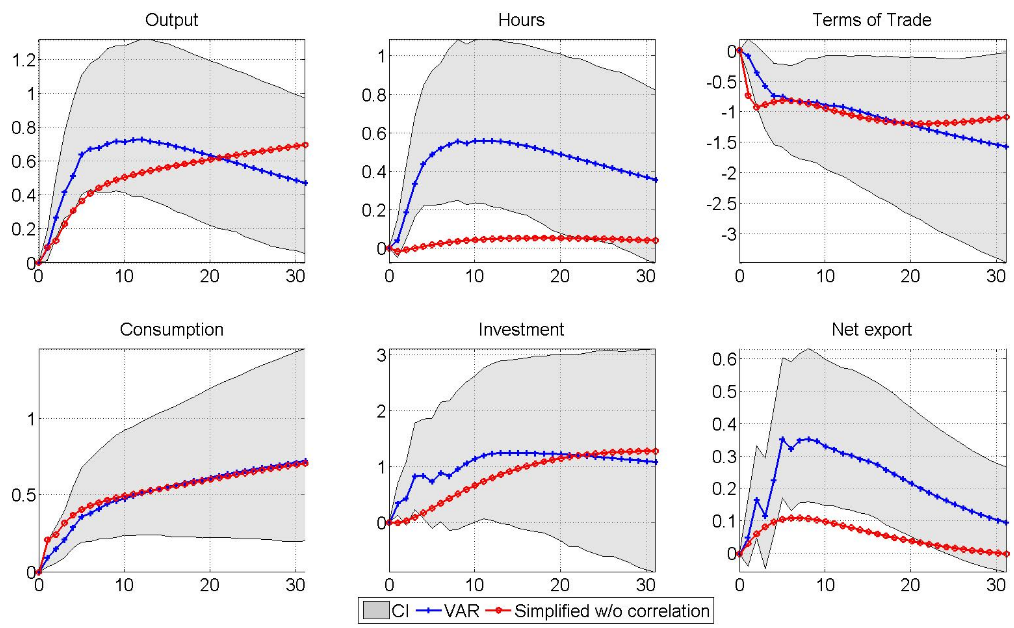


Figure 2.12: The theoretical impulse responses of the baseline model without our three key features with exogenous correlation of technology shocks to a positive U.S. shocks. Lines with plus sign is the point estimate and the shaded areas are the 95% confidence intervals. Lines with squared sign is theoretical responses from baseline model.

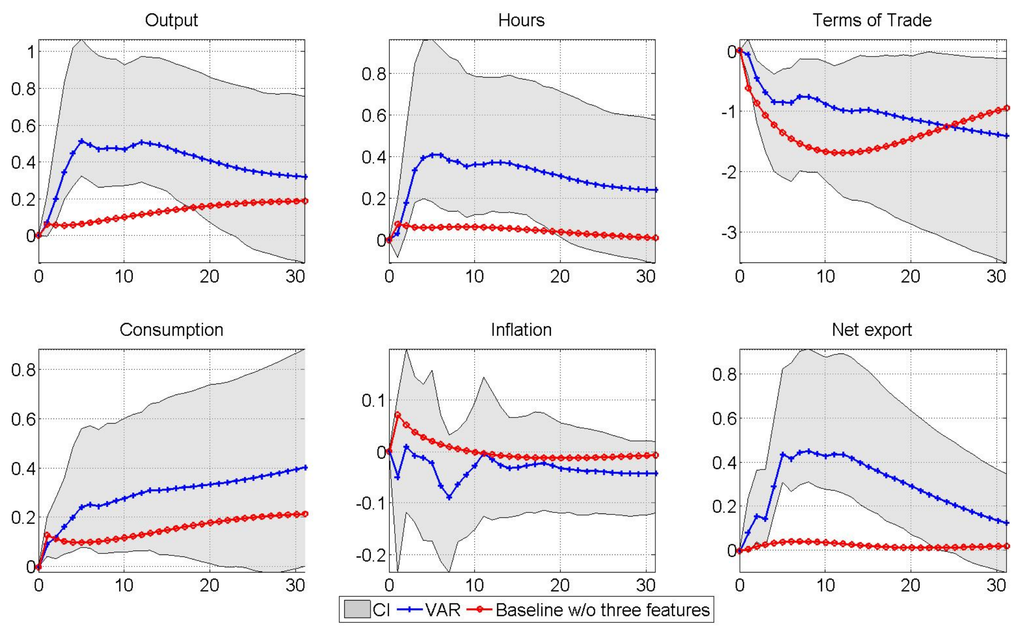


Figure 2.13: The theoretical impulse responses of the NOEM model without our three key features as we restrict the degree of price stickiness to be less than 0.75. Lines with plus sign is the point estimate and the shaded areas are the 95% *confidence intervals. Lines with squared sign is theoretical responses from baseline model.*

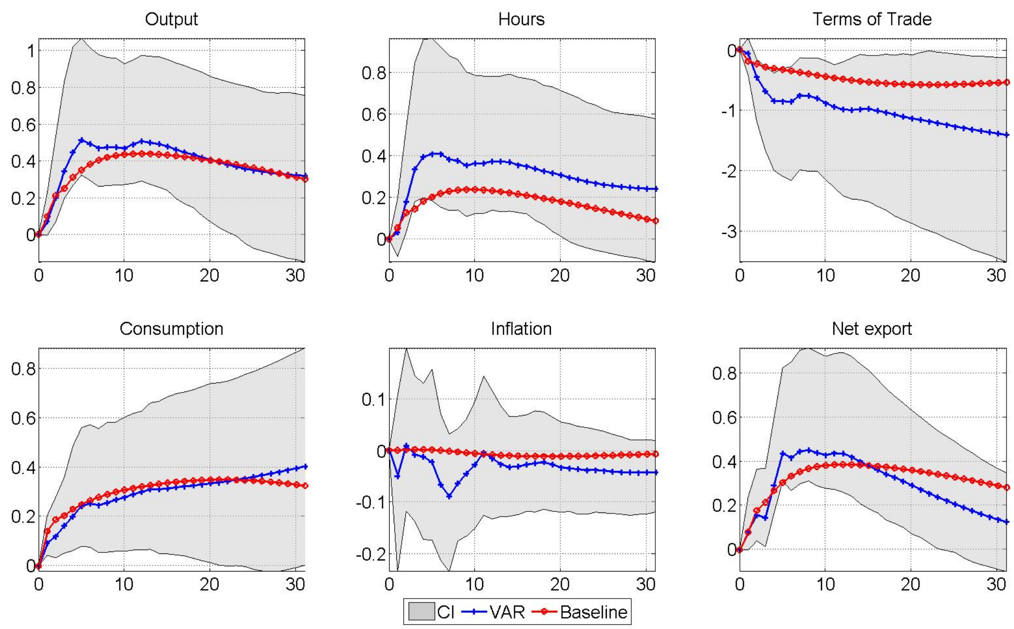


Figure 2.14: The theoretical impulse responses of the NOEM model with our three key features. Lines with plus sign is the point estimate and the shaded areas are the 95% confidence intervals. Lines with squared sign is theoretical responses from baseline model.

Chapter 3

News Shocks in Business Cycles: Evidence from Forecast Data

Wataru Miyamoto and Thuy Lan Nguyen

3.1 Introduction

A large recent literature starting from Beaudry and Portier (2006) has focused on news shocks as the main driver of business cycles. News shocks in this literature are defined as information about changes in future fundamentals that does not affect current fundamentals. When agents learn that there will be changes in exogenous fundamentals in the future, they change their current behavior, causing economic fluctuations today which in turn are observed in realized data. Therefore, the literature on news shocks has used standard macroeconomic realized data such as output and consumption to make inference about news shocks. However, since news shocks can only affect current outcomes through expectations, data on expectations should be useful in understanding the role of news shocks.

To illustrate how data on expectations can be informative about the role of news shocks, we show that news shocks can have strong implications about the movements of expectations in the model, which are different from the data. Figure 1.1 plots the realized output growth rate of the US between 1970Q1 and 2006Q4 along with the model-implied expectations of output in Schmitt-Grohé and Uribe (2012). Estimated with only realized data, the model implies that news explains about half of the fluctuations in output. As a result, there are large changes in expectations that resemble the movements of realized output. However, these movements of the model-implied expectations are significantly different from those of data on expectations, which are also plotted in Figure 1.1. First, while the model-implied expectations track the movements of realized output fairly well, data on expectations do not. For example, in the model, agents could anticipate a year in advance that output would decline in 2001. However, data on expectations suggest that agents actually expected a boom. The differences between the model-implied expectations and data on expectations are also clear in other instances such as the 1981-82 recession. Second, data on expectations are generally smoother than the model-implied expectation. Especially after 1985, there are no drastic movements in data on expectations in contrast to the more substantial changes in the model-implied expectations.

Motivated by these observations, this paper uses data on expectations to quantify the role of news shocks in business cycles. More specifically, we estimate a standard real dynamic stochastic general equilibrium model with Bayesian methods using *both* realized data *and* data on expectations. We use forecast data from the *Survey of Professional Forecasters* to measure agents' expectations in the economy and match them with the corresponding model concepts.

Our estimation shows that adding data on expectation changes the inference about news shocks significantly. We find that news shocks explain about 24% of the aggregate fluctuations in output when the estimation includes data on expectations. This estimate is about *half* of the estimated contribution of news shocks without data on expectations. Furthermore, this result is robust across a range of model specifications including models with and without nominal rigidities.

Another important finding of our paper is that the precision of the estimates greatly improves when using data on expectations, suggesting that data on expectations are useful in inferring news shocks. Without data on expectations, the contribution of news shocks to aggregate variables is imprecise. For example, the 95% confidence interval of the share of the variance of government spending explained by news shocks is between 10% and 90%. In contrast, estimated with data on expectations, this interval narrows to between 2% and 18%.

The reason for the smaller estimated contribution of news shocks and the substantial increase in precision is that data on expectations restrict the role of news shocks in driving business cycle fluctuations. In response to news shocks, the economy responds slowly until the shock materializes. Since agents know that the shock will materialize, they can expect that the largest response of output growth will be when actual changes in fundamentals materialize. In other words, their expectations about future output growth rate will move. When we observe data on expectations, we put a restriction on how large the movements of expectations in the model can be. As data on expectations are generally smooth and do not resemble realized output much, the estimation with data on expectations attributes a smaller role to news shocks than the estimation without data on expectations. This restriction is especially powerful in identifying the types of news shocks that do not create significant "Pigou cycles", which are aggregate fluctuations caused by changes in expectations when shocks have not yet materialized. An example of such news shocks in our model is news about preference shocks, which only changes expected future output but not current output. In other words, with these types of news shocks, whether agents know that the shock will happen in advance or not does not matter for their current behaviors. Therefore, without data on expectations, it is difficult to distinguish these news shocks from unanticipated shocks of the same kind, which means estimation results without data on expectations can be driven by priors. By observing how expectations move in the data, we can separate unanticipated shocks that change output immediately without changing expectations from news shocks that only change expectations, which leads to a much more precise estimate of news shocks.

Although news shocks account for about 24% of output fluctuations in the long run, news shocks are negligible in explaining the short run fluctuations before actual changes in fundamentals happen. In the model, there are two types of news shocks: those that create Pigou cycles and those that do not. News shocks that do not create Pigou cycles cannot generate substantial fluctuations in the short run. News shocks that generate Pigou cycles can potentially cause significant short run fluctuations. However, the role of these news shocks is quantitatively modest. Therefore, news shocks are not important in explaining short run fluctuations before the shock materializes, i.e. for horizons up to two years. In particular, we find that only 10% of the fluctuations of output and 7% of the fluctuations of hours within two years are explained by news shocks. The rest of the macroeconomic variations are accounted for by standard macroeconomic unanticipated shocks.

Among different types of news shocks considered, news about demand shocks is close to zero. For instance, news about preference shocks explain less than 1% of the variations of output and only 5% of the fluctuations of consumption, and news about government spending shocks explain less than 6% of the government spending variations. The reason for such a small contribution of news about demand shocks is because they do not generate substantial Pigou cycles. When agents receive news that there will be a positive preference shock in the future, they expect that future output will increase, but their current behaviors do not change significantly. Therefore, if news about demand shocks were important, we would observe that expectations of output fluctuate strongly with little change in current output. However, data on expectations do not exhibit large movements over time, so the role of news about demand shocks is negligible.

In terms of explaining the post-war business cycles in the U.S., we find that news shocks can explain to some extent the 1980 recession and the 1993-94 expansion episodes but do not explain much of other business cycles in our sample, consistent with data on expectations. In the case of 1980 recession, data on expectations show that agents had information about the consequences of an oil price increase a year in advance with the Iranian war going on. Therefore, agents anticipated that output would decline, and output actually declined as expected. However, for other business cycles in the sample, agents did not change their expectations much, resulting in news being unimportant.

The results above are robust across model specifications, further suggesting that data on expectations have substantial information to help us infer news shocks. In a version of our model with nominal rigidities, news shocks explain 28% of output fluctuations, similar to the 24% estimated in the baseline model. This result is consistent with the recent work by Milani and Rajbhandari (2012). In another variation of the baseline model where we incorporate a labor adjustment cost to better explain the movement of hours, we also find that news shocks explain about 25% of the fluctuations in output when we include data on expectations as additional observables.

Our above insights that given the movements of data on expectations, news shocks are not the main source of business cycles also carry over to models with imperfect information. This is important because Coibion and Gorodnichenko (2012a, 2012b) emphasize that rational expectation imperfect information models may be more appropriate than full information models in explaining some features of data on expectations such as persistent forecast errors. However, we argue that whether imperfect information models can fit data on expectations better, news shocks are unlikely to be a major driver of business cycles. The intuition is as follows. In imperfect information models, agents receive news about future fundamentals with a noisy signal. If the signal is accurate, agents recognize that there is a news shock, then the importance of news shocks would be about the same as in the perfect information setting, which is our baseline model. When the signal is noisy, agents do not perceive news shocks accurately, leading to small changes in their expectations. If agents' expectations do not change, agents do not change their behaviors until they actually observe the change in fundamentals. Therefore, news shocks in this case would not be able to generate substantial Pigou cycles. In other words, there is no good distinction between news shocks and unanticipated shocks, i.e. information about future fundamentals, are not important in explaining short run fluctuations.

Finally, although we only use data on expectations from the Survey of Professional Forecasters (SPF) in our estimation, we argue that our results can be robust to using other data on expectations. First, the SPF forecast data are in line with other forecast surveys such as the Blue Chip, the Consensus Forecast and the Greenbook. Second, the movements of SPF forecast data on output, which we use in the baseline, are also similar to those of Consumer Confidence, which conducts a minimum of 500 interviews each time. In other words, the SPF data can be a proxy for the expectations of agents in the economy. However, since Consumer Confidence survey does not have an explicit relationship with the defined variables in the model, we do not use those data for our estimation.

Our paper is directly related to a large literature estimating the roles of news shocks in the business cycles such as Fujiwara et al. (2010), Schmitt-Grohé and Uribe (2012) and Khan and Tsoukalas (2012) which identify the role of news shocks by observing realized macroeconomic variables. Davis (2007) and Gortz and Tsoukalas (2013) address this question using financial variables such as corporate bond spreads. Unlike those papers, we propose a new way to infer news shocks more precisely using data on expectations. Our paper is also connected with the literature which expands the observation set to more precisely estimate the model. In particular, Forni et al. (2012) show that news shocks explain less than 25% of output when including a large number of variables in a FAVAR estimation, which is similar to our results. We are related to the recent literature incorporating data on expectations in a structural model. For example, Barsky and Sims (2012) show that consumer confidence contains news about future fundamentals. Unlike them, we use data on expectations of well-defined macroeconomic variables to directly map model-implied expectations with the data to infer the role of news shocks in the economy. Our estimation finds that over 50% of data on expectations is explained by news shocks, consistent with Barsky and Sims (2012) in the sense that data on expectations contain news. Other papers such as Del Negro and Schorfheide (2012) and Del Negro and Eusepi (2012) have incorporated data on expectations in their

DSGE estimation. However, their models have no news shocks, so they cannot address the question that we are interested in. Finally, we are also related to the work of Hirose and Kurozumi (2012) and Milani and Rajbhandari (2012), who use data on expectations to quantify the role of news shocks. Besides the difference in model specifications as we use both real DSGE model and model with nominal rigidities while they use model with nominal rigidities only, we provide insights on how and when data on expectations help to distinguish news shocks from unanticipated shocks. Furthermore, we explain how our results can be robust even in an imperfect information setting.

The rest of the paper is organized as followed: Section 2 introduces data on expectations. In section 3, we describe the full model setup, followed by a discussion of the estimation methods including priors and observables in Section 4. Section 5 presents the main estimation results of the model with data on expectations and analyzes how data on expectations help to identify news shocks. We test the robustness of our results with data on expectations of different variables and time period in Section 6. We conclude the paper in Section 7.

3.2 Data on Expectations

This section describes data on expectations that we use to estimate a structural model with news shocks. We make two points about the data. First, these data on expectations are relatively smooth compared to realized data, and do not track the movements of realized data well. Second, they reflect what agents know about the current and future states of the economy.

Our data come from the *Survery of Professional Forecaster* (SPF) of the Federal Reserve Bank of Philadelphia. In the second month of every quarter, nine to forty professional forecasters are asked to report their forecasts up to four quarters ahead for output and other macroeconomic variables. This dataset contains the longest possible forecast in quarterly frequency starting as early as 1968Q4 for output while other surveys such as the Blue Chip, Consensus or Livingston forecast surveys are either in monthly frequency starting late 1980s or in semiannual frequency. We use the mean of forecasts across individual forecasters as our data on expectations.

Data on expectations have two relevant features for our study. First, data on expectations are smooth relative to realized data, and do not resemble realized data in most of the sample period. We plot in Figure 1.2 the four-quarter output growth rate together with the corresponding two- and four-quarter ahead data on expectations, denoted by $F_{t-2}\Delta \ln y_{t-4,t}$ and $F_{t-4}\Delta \ln y_{t-4,t}$, respectively. We observe that the movements of data on expectations, especially the four-quarter ahead data on expectations, do not exhibit large variations over time. Even though the two-quarter ahead data on expectations are slightly more volatile and track realized data better than the four-quarter ahead data on expectations, both are smoother than realized output. This pattern is clearer when we calculate the standard deviation of quarterly forecast relative to realized data, displayed in Table 1.1. On average, only 5% of the output growth rate fluctuations are anticipated one year in advance. Furthermore, the correlation of the data on expectations of output and the realized output growth rates are small.

Second, these data on expectations can represent actual expectations of agents in the economy. One supporting piece of information is that the SPF data are similar to other forecast survey data as shown in Figure 1.3 which plots the four-quarter ahead forecast of the four-quarter growth rate of output from the Blue Chip, the Consensus Forecast and the Greenbook survey forecast. The SPF forecast data of output growth rate move in a similar direction and magnitude as other surveys. This pattern is also true for other macroeconomic variables such as consumption and investment. Since it is possible that these surveys are from a small sample of forecasters in the economy, we plot in Figure 1.4 the four-quarter output growth rate forecast of the SPF survey against a measure of expected changes in business conditions in the next 12 months taken from the Michigan Survey of Consumer Confidence. We find that the movements of these two series are similar over time, suggesting that the SPF forecast data represent what agents expect in the economy.

Nevertheless, there are two major concerns about the forecast data. The first concern is that data on expectations exhibit persistent forecast errors. The last section of Table 1.1 displays the features of forecast errors within our sample. First, the mean of forecast errors is insignificant. Second, there is no strong evidence of persistent output forecast errors. Following Mankiw et al. (2004), we calculate the persistence of forecast errors of output by regressing forecast errors of output on the forecast errors known at the time agents make forecast. The coefficients are statistically insignificant, i.e. we cannot reject the null hypothesis that forecast errors are not persistent. This result justifies the use of output forecast in our estimation of the baseline model. Nevertheless, as a recent growing literature such as Coibion and Gorodnichenko (2012a and 2012b) suggests that rational expectation imperfect information models can better explain forecast data, we argue later that whether data on expectations come from an imperfect information setting does not affect our results in the sense that news shocks, or information about future fundamentals, are not important for business cycles.

Another concern is that these forecasters are conservative when writing down their forecasts. Coibion and Gordonichenko (2012a and 2012b) present evidence against the hypothesis that these agents smooth their forecast. Other papers in the literature such as Zarnowitz and Braun (1993) and Ang et al. (2007) also find that survey forecasts are more accurate for most variables and spans than forecasts obtained from VAR and other forecasting models. Besides, data on expectation change over time, suggesting that agents incorporate their information into their forecast. For example, forecast data move significantly in the 1970s period. Also, in the second oil price shock in the 1980 recession, agents were able to predict a year in advance that output would decline. The predicted decline in output is close to the realized decline in output, especially when the forecast was made two quarter before the recession. The reason is that forecasters knew that the war in the Middle East would disrupt the supply of oil. Also, OPEC countries announced that they would increase the price of oil for the next year. Therefore, forecasters incorporated these information to their forecast and could predict a recession in the U.S. one year in advance. Another episode is during the boom in early 1990s. This is the period where agents were optimistic with the New Economy. Therefore, they could forecast well the boom after the recession in 1991. These periods suggest that forecasters actually incorporate available information into their forecast.

3.3 The Model

This section presents the setup of our baseline model to investigate the role of news shocks in business cycles. We adopt a standard real DSGE model as in Schmitt-Grohé and Uribe (2012), which is the most influential paper using structural estimation to understand news shocks in this literature. More specifically, the model is a medium-scaled real business cycle model buffeted by seven types of shocks: preference shocks, neutral stationary and permanent technology shocks, stationary and permanent investment-specific shocks, wage markup shocks and government spending shocks. Each shock has an unanticipated component as well as four- and eight-quarter ahead news components. A k-quarter ahead news shock means that agents know at time $t-k$ that the shock will materialize at time t. The reasons for why we do not include shorter horizon news shocks such as one- or two-quarter ahead news is that it is difficult to distinguish short horizon news with unanticipated shocks. We describe briefly the model below.

The model consists of a continuum of agents who maximize the expected lifetime utility defined over the sequences of consumption C_t and hours worked h_t:

$$\max E_0 \sum_{t=0}^{\infty} \beta^t b_t \frac{\left[C_t - \kappa C_{t-1} - \psi h_t^v N_t\right]^{1-\sigma} - 1}{1-\sigma} \tag{3.1}$$

where b_t is an exogenous preference shifter, β is the discount factor, κ is the habit in consumption, $\psi > 0$ is a scale parameter, $v > 0$ is related to the Frisch elasticity, and N_t is a geometric average of current and past habit-adjusted consumption levels. The law of motion of N_t is given by:

$$N_t = \left(C_t - \kappa C_{t-1}\right)^{\gamma} N_{t-1}^{1-\gamma}. \tag{3.2}$$

This preference specification is introduced by Jaimovich and Rebelo (2009). These nest as special cases the two classes of preferences used in the literature while preserving long run balanced growth path. The parameter γ governs the wealth elasticity of labor supply. When $\gamma = 1$, we obtain the preference of the King, Rebelo and Plosser (1988). When $\gamma \to 0$, there is no wealth effect on labor supply in the absence of habit, and the utility function is of the same form as Greenwood, Hercowitz and Huffman (1988). Jaimovich and Rebelo (2009) show that γ has to be small in order to generate comovement among output, hours, consumption and investment in response to news shocks. We estimate this parameter.

Households are assumed to hold capital. The capital stock K_t evolves over time according to the following law of motion:

$$K_{t+1} = \left(1 - \delta\left(u_t\right)\right) K_t + a_t^i \left[z_t^i I_t\right] \left[1 - S\left(\frac{z_t^i I_t}{z_{t-1}^i I_{t-1}}\right)\right], \tag{3.3}$$

where I_t is gross investment in consumption unit, a_t^i is the exogenous stationary shock to the technology transforming investment goods to capital goods (stationary IST), which is also called the marginal efficiency of investment shock in Justiniano et al. (2011), and z_t^i is the exogenous stochastic IST shock (nonstationary IST). Therefore, $z_t^i I_t$ is in investment good unit. The growth rate of z_t^i is denoted by $\ln \mu_{zi,t} = \ln\left(\frac{z_t^i}{z_{t-1}^i}\right)$. Given this formulation, the price of investment is related to z_t^i by $z_t^i = \frac{P_t}{P_t^i}$.

Households can choose the utilization of capital, denoted by u_t, which means that the effective capital used every period is $u_t K_t$. However, higher utilization of capital comes with the cost of faster depreciation $\delta(u_t)$. The functional form of depreciation rate is:

$$\delta(u_t) = \delta_0 + \delta_1 (u_t - 1) + \frac{\delta_2}{2}(u_t - 1)^2,$$

where $\delta_0 > 0$ is the depreciation rate at steady state, δ_1 is set to be consistent with $u = 1$ at steady state, and $\delta_2 > 0$ is the sensitivity of capital utilization variation to the rental rate of capital.

There is a quadratic investment adjustment cost as in Christiano, Eichenbaum and Evans (2005):

$$S\left(\frac{z_t^i I_t}{z_{t-1}^i I_{t-1}}\right) = \frac{s}{2}\left(\frac{z_t^i I_t}{z_{t-1}^i I_{t-1}} - \mu_I\right)^2,$$

where $s > 0$ is a parameter and μ_I is the investment growth rate at the steady state.

The households maximize their expected utility subject to the following budget constraint:

$$C_t + I_t = D_t - E_t r_{t,t+1} D_{t+1} + w_t^h h_t + R_t^k (u_t K_t) - T_t + \Pi_t, \tag{3.4}$$

where w_t^h is the wage that households receive, R_t^k is the rental rate of effective capital, D_t is the bond holdings and $r_{t,t+1}$ is the stochastic discount factor such that $E_t r_{t,t+1} D_{t+1}$ is the period-t price of a random payment D_{t+1} in period $t+1$, T_t is the lump sum tax levied by the government to finance government expenditure, and Π_t is the profit accruing to households from ownership of the firms.

Final good Y_t is produced using the following homogeneous degree 1 production function:

$$Y_t = a_t^n \left(u_t K_t\right)^{\alpha_k} \left(z_t^n h_t\right)^{\alpha_h} \left(z_t^n L\right)^{1-\alpha_k-\alpha_h}, \tag{3.5}$$

where K_t and h_t denote the amount of capital and labor employed, L is a fixed factor that can be interpreted as land, a_t^n is the neutral stationary technology shock and z_t^n is the neutral labor-augmenting technological progress. The fixed factor of production allows for decreasing returns to scale in the variable factors of production. The growth rate of z_t^n is denoted by $\ln \mu_{zn,t} = \ln \left(\frac{z_t^n}{z_{t-1}^n}\right)$.

In the labor market, each household is a monopolistic supplier of differentiate labor $h_t\left(j\right)$. A large number of employment agencies combine the differentiated labor $h_t\left(j\right)$ into a homogeneous labor input sold to intermediate firms according to:

$$h_t = \left[\int_0^1 h_t\left(j\right)^{\frac{1}{\eta_{w,t}}} dj\right]^{\eta_{w,t}}, \tag{3.6}$$

where η_w is the elasticity of substitution. The elasticity $\eta_{w,t}$ follows an exogenous stochastic process. Since $\eta_{w,t}$ is the desired markup of the wage over the households' marginal rate of substitution, the literature refers to this as a wage markup shock which helps to explain the movement of hours. Profit maximization by the perfectly competitive employment agencies implies that the labor demand function is

$$h_t\left(j\right) = \left(\frac{W_t\left(j\right)}{W_t}\right)^{-\frac{\eta_w}{\eta_w-1}} h_t, \tag{3.7}$$

and the wage paid by firms for their labor input is:

$$W_t = \left[\int_0^1 W_t\left(j\right)^{-\frac{1}{\eta_w - 1}} dj \right]^{-(\eta_w - 1)}. \tag{3.8}$$

From the labor supply side, the problem of labor supply of type j is to maximize $\left(W_t(j) - w_t^h\right) h_t\left(j\right)$ subject to the labor demand function above. Then, the optimal condition requires

$$w_t^h = \frac{W_t}{\eta_{w,t}},$$

which means that the wage rate that households receive is smaller than the wage paid by firms.

We assume that government spending is determined exogenously and financed by a lump-sum tax. Government spending G_t has a trend X_t^G, so $g_t = \frac{G_t}{X_t^G}$ is the detrended government spending. The trend of government spending is assumed to be smoother than that of output X_t^Y and is given by:

$$X_t^G = \left(X_{t-1}^G\right)^{\rho xg} \left(X_{t-1}^Y\right)^{1-\rho xg}, \tag{3.9}$$

where ρxg is the parameter determining the smoothness of X_t^G.

All seven shocks, namely stationary and permanent neutral technology shocks, stationary and permanent investment-specific technology (IST) shocks, preference shocks, wage markup shocks and government spending shocks, include an unanticipated and news component. The news component consists of four- and eight-quarter ahead news shocks, meaning that agents receive information at time t that the shock will happen at time $t+4$ for four-quarter ahead news shocks and $t+8$ for eight-quarter ahead news shocks. Therefore, all exogenous shocks

x_t evolve over time with the following law of motion:

$$\ln\left(\frac{x_t}{x}\right) = \rho_x \ln\left(\frac{x_{t-1}}{x}\right) + \varepsilon^0_{x,t} + \varepsilon^{t-4}_{x,t} + \varepsilon^{t-8}_{x,t}, \tag{3.10}$$

where $x = \{a_n, \mu_{zn}, a_i, \mu_{zi}, \eta_w, b, g\}$, $\varepsilon^0_{x,t} \sim N\left(0, (\sigma^0_x)^2\right)$ denotes unanticipated shocks known at time t, $\varepsilon^{t-4}_{x,t} \sim N\left(0, (\sigma^4_x)^2\right)$ and $\varepsilon^{t-8}_{x,t} \sim N\left(0, (\sigma^8_x)^2\right)$ are the four- and eight-quarter ahead news shocks, respectively.

3.4 Estimation

We estimate the model using Bayesian methods with U.S. data between 1955Q1 and 2006Q4. The length of data is dictated by the available observables although we later show that our results are robust to different data periods. We estimate a subset of the deep structural parameters of the model such as those governing the shock processes.

3.4.1 Calibrated Parameters

As is common in the literature, we calibrate the parameters that are related to the steady state or often calibrated in the literature as shown in Table 1.2. The discount factor is set to be 0.99. The capital elasticity of the production, α, is set to be 0.225, implying that the labor share is 0.67 given the degree of decreasing returns to scale. This setting does not matter for our results as our robustness check shows that a constant returns to scale production without fixed capital L would yield similar results. Following previous literature, we adopt log utility function, i.e. the risk aversion parameter, σ, is 1. The depreciation rate at the steady state, δ_0, is 0.025, implying that about 10% of capital is depreciated annually. We calibrate δ_1 such that in the steady state, utilization is 1. The parameter ψ is then set such that hours worked at the steady state is 0.2. The steady state growth rates of output and investment, and the steady state share of government spending in total output are set to be equal to the corresponding U.S. data average between 1955Q1 and 2006Q4.

3.4.2 Bayesian Estimation

The rest of the parameters are estimated using Adaptive Random Walk Metropolis Hasting as discussed in Haario et al. (2001) to obtain a more efficient estimation. As in standard Bayesian estimation, we have to assign priors. Following Schmitt-Grohé and Uribe (2012), we set our priors to be the same as theirs as reported in Table 1.2. Given the priors for the parameters and the sample data Y, we can draw from the posterior distributions of the estimated parameters, denoted as Θ. This requires the evaluation of the product of the likelihood function and prior distributions, which is denoted by $L(Y|\Theta)\,P(\Theta)$. The likelihood function $L(Y|\Theta)$ is found numerically after solving the model using first order approximation method in Schmitt-Grohé and Uribe (2004). We obtain the following state space form:

$$\begin{aligned} X_{t+1} &= h_x(\Theta)\,X_t + \eta(\Theta)\,\varepsilon_t \\ obs_t &= g_x(\Theta)\,X_t + me_t^{obs}, \end{aligned}$$

where X_t is a vector of state variables and ε_t is a vector of structural shocks with $N(0, I)$, I is the identity matrix, and obs_t are the observables discussed below, and me_t^{obs} are the corresponding measurement errors.

To understand how data on expectations change the inferences about the news shocks, we estimate the model with two observable sets. The first set includes seven observables:

$$[\Delta \ln y_{t-1,t}, \Delta \ln c_{t-1,t}, \Delta \ln I_{t-1,t}, \Delta \ln h_{t-1,t}, \Delta \ln TFP_{t-1,t}, \Delta \ln p_{inv,t-1,t}, \Delta \ln G_{t-1,t}],$$

which is the quarterly growth rates of output, consumption, investment, hours, TFP, price of investment and government spending, respectively. These observables are matched with the corresponding model concepts. We only allow measurement errors, me_t^y, for output growth rate to take into account the fact that we ignore the net exports component of output. The measurement error for output growth is assumed to be an i.i.d. innovation with mean zero and standard deviation me^y, which is also estimated. We restrict me^y to be at most 10% of the standard deviation of output growth rate.

The second set of observables consists of nine observables: the seven observables above and data for two- and four-quarter ahead expectation of output growth rate. More specifically, the data on expectation used in the estimation are defined as follows: let $\Delta \ln y_{t,t+k}$ denote the average growth rate of output between t and $t+k$, i.e. $\Delta \ln y_{t,t+k} = \frac{\ln\left(\frac{y_{t+k}}{y_t}\right)}{k}$ for $k = 1, 2, 3, 4$. Then, $E_t \Delta \ln y_{t,t+k}$ is the model expectation at horizon k, or $k-$period ahead expectation, of the cumulative growth rate made at time t, and $F_t \Delta \ln y_{t,t+k}$ is the forecast of $\Delta \ln y_{t,t+k}$ at horizon k made at time t. The data and the model concept of expectations are linked by the following equations:

$$F_t \Delta \ln y_{t,t+2} = E_t \Delta \ln y_{t,t+2} + me_t^{y2}, \tag{3.11}$$

$$F_t \Delta \ln y_{t,t+4} = E_t \Delta \ln y_{t,t+4} + me_t^{y4}, \tag{3.12}$$

where me_t^{y2} and me_t^{y4} are the measurement errors for two- and four-quarter ahead data on expectations, respectively. The measurement errors for data on expectations are assumed to be i.i.d. innovation with mean zero and standard deviations me^{y2} and me^{y4}, respectively. We allow me^{y2} and me^{y4} to be no more than 10% of the standard deviation of the corresponding data on expectations. Since we do not have data on expectations dating back to 1955Q1, we treat data on expectations as missing data points between 1955Q1 and 1970Q1. We also check that having the earlier period 1955Q1-1970Q1 with the missing data points does not affect our results.

We numerically evaluate the likelihood function $L(Y|\Theta)$ by applying the Kalman filter to this state space form. Evaluating prior distribution $P(\Theta)$ is straightforward using the known distributions discussed above. Using the Adaptive Random Walk Metropolis Hasting method, we update the chains multiple times to increase efficiency of the estimation. We perform several checks to make sure the estimation has converged. In total, we have four chains of 180,000 draws each. All of our results below are computed from the last 50,000 draws of those four chains. The results do not change if we use longer chains.

3.4.3 Estimated Parameters and Model Fit

First, the parameters governing the investment adjustment cost, habit, wealth elasticity of labor supply and utilization cost do not change when estimated with data on expectations. As displayed in Table 1.3, the posterior median of the parameters estimated with and without forecast for s, κ, γ, and $\frac{\delta_2}{\delta_1}$ are similar between the two cases.

Second, the main differences between the two cases are the shock parameters, meaning that adding data on expectations mostly changes the shock processes driving the economy. The standard deviations of news for both government spending and preference shocks at four- and eight-quarter ahead are much smaller when estimated with data on expectations than without data on expectations while the standard deviations of the unanticipated shocks become larger. This result indicates that the role of news about preference and government spending shocks is smaller than before. However, the standard deviations of some news shocks become larger, which means that data on expectations change the timing of shocks. For example, the standard deviation of the eight-period ahead wage markup news shocks is larger in the case estimated with data on expectations than without data on expectations. Importantly, the estimated parameters with data on expectations are more precisely estimated than without data on expectations in the sense that the 5-95% credible sets are smaller. This result suggests that data on expectations add strong restriction to the estimation to recover the states of the economy including news shocks.

In terms of model fit, we find that the model estimated with data on expectations matches the empirical second moments well, similar to the model estimated without data on expectations. In Table 1.4, we report the medians of the posterior distributions of the population second moments computed from the last 200,000 draws of the posterior distributions in both cases together with the corresponding empirical second moments. The estimated model with data on expectations is able to replicate most of the second moments of the data. In particular, it does a better job in matching the second moments of consumption than the estimated model without data on expectations. Nevertheless, both estimated models do not capture the persistence of hours and the correlation of hours with output in the data.

3.5 News shocks and Business Cycles

This section discusses the role of news shocks in business cycles and highlights the role of data on expectations in identifying news shocks. In particular, we show that news shocks play a much less important role in explaining the fluctuations of macroeconomic variables in the model estimated with data on expectations than estimated without data on expectations. We interpret the results to explain the features of data on expectations that help to identify news shocks in the model.

3.5.1 The Contribution of News Shocks in Business Cycles

The model estimated with data on expectations attributes a smaller contribution of news shocks than the model estimated without data on expectations. To facilitate the comparison between the two cases, we report in the first and second columns of Table 1.5 the shares of the unconditional variances of output, consumption, investment and hours growth rates explained by all types of news shocks in the model estimated without and with data on expectations between 1955Q1 and 2006Q4. All of these results are computed as the mean of the posterior distributions of the variance decomposition, together with their 5-95% credible sets.

The total contribution of news shock to U.S. output fluctuation is about half of the estimated contribution without data on expectations. News shocks account for about 24% of output growth rate, compared with 43% estimated without data on expectations. Decomposing the contribution of each type of news shocks, we find that news about preference, government spending shocks, and wage markup shocks to some extent become much less important than in the model estimated without data on expectations. For example, news about preference shocks explain about 1% of output variation compared to 9% without data on expectations, and news about wage markup shocks explain only 7.5% of output variation, which is half of the contribution estimated without data on expectations.

To gauge how much news shocks explain past business cycles, we compute the historical decomposition of the U.S. output between 1955 and 2006. We find that most of the business cycles in our sample are not driven by news shocks. Figure 1.5 plots the historical decomposition for news shocks along with the time series of the four-quarter U.S. output and the corresponding four-quarter ahead forecast. Two exceptions are the 1980-81 recession and

1992-93 expansion. This result is consistent with the timing of data on expectations which show that agents could predict correctly the movements of output a year in advance. For example, in the second oil price shock, agents read news about the Iranian war in 1979 and announcement about oil prices, so they could anticipate a year in advance that output would decline, which was true in 1980. Therefore, news shocks are estimated to be important in that recession. However, the fact that news shocks do not account for most of the output fluctuations during this sample period suggests that news shocks are not the main source of business cycles.

Data on expectations also have a large impact on the inference about the contributions of news shock to both consumption and government spending: news shocks are negligible in the model estimated with data on expectations. Only 11% of the consumption volatility is explained by news shocks compared to 53% estimated without data on expectations. Similarly, news shocks account for less than 8% of the variations in government spending, in contrast with 58% estimated without data on expectations. The reason for these substantial decline in the role of news shocks is that news for preference and government spending shocks is much less important than before, 4% and 5% respectively, while unanticipated shocks of the same type of shocks become more important.

However, even when estimated with data on expectations, news shocks remain relatively important in explaining the movements of hours, contributing 46% to the variations of hours growth rates, respectively. Without data on expectations, news shocks explain 76% of hours, meaning data on expectations also reduce the importance of news shocks to aggregate fluctuations but to a lesser extent compared to consumption and government spending. The total contribution of news shocks to hours remain large because the important news shocks, i.e. stationary investment specific technology shocks and wage markup shocks, are able to generate the delayed responses of hours to output as documented in Schmitt-Grohé and Uribe

(2012). These news shocks cause immediate changes in output and consumption while hours worked adjust slowly. In fact, the immediate response of hours is negligible and takes place mostly when fundamentals actually change. Therefore, the model assigns a non-negligible role to these news shocks.

Besides changing the total contribution of news shocks to aggregate fluctuations, data on expectations also changes the estimated timing of news shocks. For example, without data on expectations, the four- and eight-quarter ahead news shocks explain equal fractions of the aggregate fluctuations while the model estimated with data on expectations assigns a larger role to the eight-quarter ahead news shocks.

Lastly, although news shocks do not explain a large fraction of output fluctuations, we find that news shocks explain a large share of the volatilities of data on expectations. More specifically, 53% and 57% of the fluctuations in the two-quarter and four-quarter ahead forecast of output growth rate are explained by news shocks. This result is consistent with our intuition that forecast contains information about news shocks, similar in spirit to Barsky and Sims (2010), who show that consumer confidence contains news about future productivity. In our case, the important news shocks for the variations of data on expectations are news about wage markup and stationary investment-specific technology shocks.

3.5.2 The Precision of the Estimates

One of our central findings is that the contribution of news shocks for all variables are much more precisely estimated with data on expectations than without data on expectations. We plot in Figure 1.6 the posterior distributions of the shares of output, consumption, investment, hours and government spending explained by news shocks with and without data on expectations as well as the prior distributions. The posterior distributions of the shares of the unconditional variance of the growth rates of all variables are tighter when estimated with data on expectations than without data on expectations. The difference between the posterior distributions of the two cases is especially significant for consumption and government spending: the posterior distributions without data on expectations are similar to the prior distributions and flat between 0 and 100% while those with data on expectations are tightly estimated to be under 20%. In other words, without data on expectations, the estimates are highly influenced by priors, and since data on expectations give a lot of information about what agents know in advance, we obtain a much more precise estimate for the role of news shocks.

3.5.3 The Importance of News Shocks in the Short Run

Even though news shocks can explain around 24% of the unconditional variance of output, news shocks play a much more negligible role in explaining short run fluctuations. We focus on horizons up to two years because this is when agents know that the shock will happen but has not yet materialized. As shown in Figure 1.7 which plots the forecast error variance decomposition of news and unanticipated shocks for the growth rates of output, consumption, investment and hours[1], news shocks explains less than 10% of all the macroeconomic variables for up to two year horizons. The reason is that although some of the news shocks such as news about future productivity shocks can cause changes in output today, these news shocks play a negligible role in business cycles. Other types of news shocks such as government spending news shocks do not cause agents to adjust their current behaviors significantly, resulting in a small fraction of output being explained by news shocks in the short run. The forecast error variance decomposition for hours illustrates our intuition more clearly. In the case of hours, news about wage markup shocks is the most important news shocks but

[1] In the forecast error variance decomposition for the *level* of output, consumption, investment and hours, we also find a small role of news shocks in the short run in the two year horizon.

does not affect hours much until wage markup shocks actually materialize. Therefore, even though news shocks explain nearly half of the movements in hours in the long run, it explains almost nothing of hours in the short run, and we obtain the result that the importance of news shocks for hours jumps at horizon 4 and 8

We note that news shocks play a much smaller role in the short run when estimated with than without data on expectations. Without data on expectations, news shocks in the short run explain up to 25% of output fluctuations. However, as adding data on expectations reduces the importance of news shocks overall, the role of news shocks in the short run becomes much smaller than estimated without data on expectations.

3.5.4 The Role of Data on Expectations in Inferring News shocks

This section explains how data on expectations change the inference about news shocks and help us obtain a much more precise estimate. The intuition behind our results is as follows. If news shocks were a major driver of business cycles, expectations would exhibit movements that resemble realized output. Since data on expectations do not have large movements over time and do not resemble realized output, news shocks cannot be the main source of fluctuations. This intuition especially works to help us distinguish news shocks such as preference and government spending news shocks, which are hard to distinguish from unanticipated shocks of the same kind without data on expectations.

In the model, there are two types of news shocks that are different in terms of how agents respond to the news before shocks actually materializes. We call the first type "non-Pigou cycle" news shocks, which are news shocks that do not generate substantial aggregate movements until fundamentals actually change. In our model, news about demand shocks such as preference and government spending news shocks falls into this "non-Pigou cycle" category. To understand how data on expectations help to identify these news shocks, we plot the responses of output growth rate to both unanticipated and news for these two shocks in the first two panel of Figure 1.8. Given the response of output growth rate, the response of the four-quarter ahead expectations made at time t is the same as the response of output growth rate at time $t+4$ in our perfect information setting. These responses exhibit two distinct characteristics. First, in response to an unanticipated shock, output growth rate increases immediately and four-quarter ahead expectations of output growth rate do not change much, which is due to the transitory nature of the shock process. Second, in response to a four-quarter ahead news shock, there is not much "Pigou cycle" generated, i.e. agents do not change their behaviors much until fundamentals actually change. The responses of output to a news shock look just like their responses to an unanticipated shock shifted by four periods. In other words, the only thing that move at time t when agents learn about the news shock is their four-quarter ahead expectations. As whether agents know in advance about these shocks going to happen in the future does not affect their current behaviors, observing output growth rate only is not informative about the timing, so it is difficult to distinguish news shocks from unanticipated shocks. However, if we observe additionally data on expectations, we can tell apart news shocks, which change expectations substantially, from unanticipated shocks, which do not have much impacts on expectations. Therefore, without data on expectations, the contributions of preference and government spending news shocks are imprecisely estimated and driven by priors; and once we add data on expectations in the observable set, we obtain a much more precise estimate for these news shocks. Furthermore, since expectations react strongly to news shocks, the fact that we observe expectations puts a restriction on how large news shocks can be. As data on expectations are relatively smooth, news shocks of these types cannot be important, which explains why the importance of preference and government spending news shocks is much smaller when we estimate the model with data on expectations.

The second type of news shocks is the "Pigou cycle" news shocks, which include stationary and nonstationary TFP shocks among others. The main difference between this type of news shocks and the "non-Pigou cycle" news shocks is that output growth rate responds immediately to the news shocks as shown in the third to last panel of Figure 1.8. In response to an unanticipated shock such as an unanticipated stationary TFP shock, output growth rate increases right away while four-quarter expectations do not move as much. Output growth rate also increases immediately after a stationary TFP news shock but this increase is gradual and peaks in period five when TFP actually increases. Therefore, in theory, observing output can help distinguish news shocks from unanticipated shocks of this type. Nevertheless, it is possible for the estimation to interpret the responses of output growth rate to news shocks as the responses to two consecutive unanticipated shocks. Therefore, observing additionally data on expectations is still helpful. For example, data on expectations of TFP would help pin down news about TFP shocks as news would lead to expected movements in TFP. In our case, we only observe data on expectations of output but these data still add more information about the timing of the shock since expectations of output react strongly to news shocks. Since data on expectations are smooth relatively to the actual output, this type of news shocks turns out to be not important either.

A natural question is then if there is any situation in which adding data on expectations does not change the inferences about news shocks, its importance and the precision of the estimates. When news shocks generate strong immediate responses of output, i.e. shocks that can generate substantial "Pigou cycles", but do not change expected future output, including data on expectations of output or endogenous variables as observables in the estimation may not change the contribution of news shocks compared to the results obtained without data on expectations. An example of this type of news shocks is news about future TFP shocks in a model where prices are substantially sticky. The intuition is that in an extreme case when prices do not change at all, output will increase immediately after a TFP news shock. Since agents know that technology will increase in the future, they demand more goods from today. The demand is higher when price is fixed, causing output to increase strongly from today. In this case, under some shock process parameters, the four-quarter ahead expectations of output growth rate will not respond much, consistent with the movements of data on expectations. Therefore, adding data on expectations of output into the observable set may not change the inference of news shocks[2]. This problem arises because we only observe data on expectations of endogenous variables such as output. If we can observe data on expectations of exogenous variables such as TFP, these "Pigou cycle" news shocks would be better identified.

However, in general, only under extreme parameterization can we obtain news shocks that generate such strong Pigou cycles that data on expectation cannot help to better identify. As shown in Figure 1.8, in our baseline model, for all types of news shocks including news about productivity shocks, expectations of output growth rate fluctuate significantly as the peak response happens at the time that the shock materializes, which explains why data on expectations help to better identify all types of news shocks in our model. We explore later in our Robustness section if data on expectations are still helpful in our estimation for the role of news shocks in models with nominal rigidities.

3.6 Robustness

This section provides the robustness of our results with respect to different data period, data vintages, and data on expectations. We also show that our result is robust with a wider range of models when we include nominal rigidities or labor adjustment cost in the model. Finally,

[2]In this case, we can identify news shocks by observing key aggregate variables.

we offer intuition why our results do not change under imperfect information assumption.

3.6.1 Data Period

Column 1 of Table 1.7 presents the estimated importance of news shocks using data from 1970Q1 to 2006Q4 to avoid missing data on expectations. Similar to the baseline model, our estimation of the model with data on expectations predict that news shocks account for nearly 27% of output fluctuations, 15% of consumption, 30% of investment and 40% of hours. The posterior distributions of the shares of the variances of these variables are also tightly estimated. Consistent with our explanation above, news about demand shocks are negligible. Other results such as the negligible role of news shocks in short run fluctuations also carry over to this case. This result suggests that data on expectations are informative, so whether to include the 1955Q1 to 1969Q4 or not does not alter the conclusion about the role of news shocks in business cycles[3].

3.6.2 Realized Data Vintages

Since data are released with different vintages and agents form forecast when they only know the first releases of realized data, we re-estimate the model using first release realized data instead of the revised data as in our baseline estimation. All of the results in our baseline estimation are robust to this change in data as shown in Column 2 of Table 1.7, which displays the result of the baseline model estimated with output, consumption, investment and government spending data between 1955Q1 and 2006Q4 using its first vintage from the Federal Reserve Bank of Philadelphia. In particular, all types of news shocks explain about 18% of output growth rate, 5% of consumption, 28% of investment, and 45% of hours,

[3]We also verified that our results are robust with constant returns to scale production function, as well as 1984Q1-2006Q4 period.

implying that news shocks are not the major source of business cycles. The fact that our results are robust with respect to different data vintages suggests that whether forecasters try to forecast first or revised release does not matter much.

3.6.3 Types of Data on Expectations

We consider different types of data on expectations that can be used as observables such as data on expectations of different horizons and data on expectations of all the aggregate variables.

Expectation Horizons

Columns 3 and 4 of Table 1.7 show that the baseline estimation results are robust when using only four-quarter ahead data on expectations or all of the one-, two-, three- and four-quarter data on expectations. Compared to the baseline model, both cases predict a similar importance of news shocks to business cycles. The precision of these estimates are also in line with the baseline results. Although using all horizons of data on expectations lead to tighter estimated contribution of news shocks to consumption and government spending, the rest of the results remains the same as our baseline model. These findings suggest that four-quarter ahead data on expectations alone are helpful in inferring news shocks. The intuition is that since we include four- and eight-quarter ahead news shocks in the model, the four-quarter ahead data on expectations summarize the information agents have about the economy a year ahead. Although observing additionally the eight-quarter ahead data on expectations compared to only the four-quarter ahead can give us more information about the timing of eight-quarter ahead news shocks, the four-quarter ahead data on expectations still help to infer news shocks of horizons longer than four. If, on the other hand, our model includes two-quarter ahead news shocks, data on expectations with shorter horizons are important to help better identify these news shocks.

Other Data on Expectations

Since the SPF data contain forecasts of other variables such as consumption, investment and government spending, we estimate the baseline model using two- and four-quarter ahead data on expectations of these variables in addition to the data on expectations of output. The result of this robustness exercise is reported in Column 5 of Table 1.7. In this case, news shocks contribute to about 20% of output fluctuations and less than 10% to consumption fluctuations. Also, data on expectations of government spending point to an even smaller contribution of news shocks to government spending than the baseline estimation: in fact, the role of news shocks is close to zero. That our baseline estimates are robust to adding more data on expectations as observables suggests that data on expectation for output are informative about the role of news shocks. This result together with the result estimated using different horizons of data on expectations of output suggest that the four-quarter ahead data on expectations for output alone are useful to infer the role of news shocks in business cycles in our case.

3.6.4 The Role of News Shocks To Hours

We analyze why news shocks remain important for hours, explaining over 40% of hours fluctuations. To that end, we first show that data on expectations about the labor market suggest that news shocks may not be the major source of uncertainty for hours. Furthermore, the importance of news shocks to hours decreases once we augment the model with a labor adjustment cost, suggesting that further incorporating data on expectations from the labor market can be helpful in determining the role of news shocks for hours.

In the model, since news shocks have largest impact on hours when the shock has materialized, data on expectations of hours worked would be informative about the role of news shocks on hours. In particular, if news shocks were as important to hours as in our baseline estimation, the model-implied expectations of hours would have large movements that resemble realized hours movements. Therefore, comparing the model-implied and data on expectations of hours would shed light on the possible role of news shocks. However, we do not have sufficient data on expectations of hours or employment, so we resort to the change in unemployment rate and its expectations in the SPF survey plotted in Figure 1.9. Similarly to output, data on expectations of the change in unemployment rate are smooth and do not track the movements of realized unemployment rate change, which suggests that agents in the economy do not have much information about the future movements in the labor market. In contrast, when the model is estimated with data on expectations of output, the four-quarter ahead model-implied expectations of hours growth rate, plotted in Figure 1.10, have significant movements over time that track the movements of realized hours growth rate well because news shocks explain 46% of hours fluctuations. In other words, we may have overestimated the role of news shocks for hours worked.

The reason for why news shocks are estimated to be important for hours is that news shocks help to explain the persistent and delayed responses of hours relative to output in the data. The second moments implied by the model presented in Table 1.4 show that the persistence of hours is much lower than in the data. However, conditional on wage markup news shocks, we find that this type of news shocks helps to explain the persistence of hours and the delayed response of hours compared to output, so there is a tension between fitting the movement of hours worked and the movement of expectations. Therefore, the estimation assigns a non-negligible role of news shocks to hours. Without any change in the model in the labor market to explain hours worked, the model needs wage markup news shock to help explain the data even when we observe data on expectations[4].

Motivated by our analyses above, we augment the baseline model to include a labor adjustment cost to account for the behavior of hours and estimate this augmented model, "model with LAC". For simplicity, the labor adjustment cost is of the quadratic form as follows:

$$\phi(h_t, h_{t-1}) = \phi_H \left(h_t - h_{t-1}\right)^2 ,$$

where $\phi_H > 0$ is the parameter governing the adjustment cost. Labor adjustment cost can change the model's behavior in two ways. The first is that the responses of hours can be more persistent and delayed in response to unanticipated shocks depending on how large the labor adjustment cost is. This implies that news shocks may not be necessary to explain hours. However, labor adjustment cost can also make news shocks more important. The reason is that upon receiving news that exogenous fundamentals will change in the future, agents change their labor supply today. Therefore, news shocks may generate substantial Pigou cycles, i.e. stronger movements of output before the shock materializes. In that case, news shocks can be more important than the 24% reported in the baseline estimation and still be consistent with data on expectations.

When estimating the augmented model with labor adjustment cost, we find that the data prefer this model to the baseline model in terms of log marginal likelihood, and the estimated parameter of the labor adjustment cost, ϕ_H, is significantly different from zero. Furthermore, this model has a better fit in terms of matching empirical second moments. As reported in the last row of each panel in Table 1.4, this augmented model can explain the persistence of hours as well as the correlation of hours and output.

[4]A recent paper by Khan and Tsoukalas (2012) also finds that in a New Keynesian model similar to Schmitt-Grohé and Uribe (2012) model, wage markup news shocks specifically continue to play a significant role explaining hours worked. Their findings suggest that sticky prices framework is not the answer to explain hours movement, so the model would still resort to wage markup news shocks to be able to explain hours.

In terms of the importance of news shocks, the estimation assigns a smaller contribution of news shocks to hours than the baseline estimation. In particular, news shocks account for about 33% of hours fluctuations, compared to 46% in the baseline model as reported in Column 3 of Table 1.5. The contributions of news shocks to other variables are, nevertheless, similar to the baseline model. For example, the estimation attributes about 25% of the variations in output to news shocks, consistent with our baseline estimation. The estimated importance of news shocks for consumption, investment and government spending is also similar to the baseline model.

The results of this model with labor adjustment cost suggest that the importance of news shocks to hours can be sensitive to the specification of the labor market. Additionally, since the confidence interval of the estimate for the role of news shocks in hours worked is relatively wide, incorporating data on expectations of unemployment into the estimation can be helpful to further understand the role of news shocks in explaining the variations of hours.

3.6.5 Models with Nominal Rigidities

In this section, we show that data on expectations are also informative about the role of news shocks in models with nominal rigidities, and the estimated model with nominal rigidities predicts a similar contribution of news shocks to aggregate fluctuations. To this end, we augment the baseline model with Calvo-type sticky prices and wages. We additionally add three types of shocks: price markup shocks, persistent interest rate target shocks and identically independent monetary policy shocks. Unlike the seven shocks in the baseline model, these three shocks do not have any news component.

Similar to the baseline model, we estimate this model using Bayesian methods for two cases. The first case is without data on expectations which includes ten observables: the seven observables in the baseline estimation and inflation, growth rates of real wage and nominal interest rate:

$$[\Delta \ln y_{t-1,t}, \Delta \ln c_{t-1,t}, \Delta \ln I_{t-1,t}, \Delta \ln h_{t-1,t}, \Delta \ln TFP_{t-1,t},$$
$$\Delta \ln p_{inv,t-1,t}, \Delta \ln G_{t-1,t}, \pi_{t-1,t}, \Delta \ln W_{t-1,t}, R_t]$$

The second case includes 14 observables, consisting of the ten observables above and the data of two- and four-quarter ahead expectations of output and inflation from the SPF.

As reported in the last column of Table 1.7, the estimated model with data on expectations attributes about 28% of output fluctuations to news shocks, which is in the similar range estimated in the baseline model without nominal rigidities. The contributions of news shocks to consumption and investment are also similar to the real model. An interesting note is that news now explains only about 14% of hours growth rate, supporting our conclusion that the role of news shocks to hours may be sensitive to the model's ability to replicate the behaviors of hours. Also consistent with the baseline estimation, data on expectations help to estimate the role of news shocks much more precisely. In Figure 1.11, we plot the prior distributions as well as the posterior distributions of the shares of the variances of output, consumption, investment, hours and government spending estimated with and without data on expectations. The precision of the estimates of the role of news shocks increases greatly for all variables when the model is estimated with data on expectations. We also find that news shocks are negligible in explaining short run fluctuations and news about preference and government spending shocks are almost nil in this model with nominal rigidities. These results are consistent with our baseline estimates.

The reason for why we obtain similar results to the baseline estimation is that even in the model with nominal rigidities, data on expectations put strong restrictions in the estimation which help to distinguish news shocks from unanticipated shocks. It turns out that in this model with nominal rigidities, preference and government spending news shocks are also "non-Pigou cycle" shocks, which makes it difficult to distinguish them from unanticipated shocks of the same kind without data on expectations. Therefore, when we observe additionally data on expectations, we are able to separate news from unanticipated shocks. Also, although under extreme parameterization such as fixed prices, "Pigou-cycle" news shocks such as news about stationary TFP shocks may cause substantial change in output today without changing expected future output, the data inform us that the "Pigou-cycle" news shocks still lead to substantial changes in expected future output. Therefore, data on expectations are still helpful in inferring news shocks in this case. As data on expectations are relatively smooth, the role of these news shocks are negligible and precisely estimated.

3.6.6 Imperfect Information and Data on Expectations

Finally, we discuss the sensitivity of our results with respect to the assumption of perfect information. In particular, our maintained assumption of the paper is that agents have perfect information about news about the future as well as the current states of the economy and estimate the model using data on expectations. However, Coibion and Gorodnichenko (2012a and 2012b) suggest that rational expectation imperfect information models are more appropriate to explain the behavior of data on expectations than rational expectation perfect information models. We argue that news shocks cannot be a major driver of business cycles in the imperfect information setting. The intuition is that if agents have an imprecise knowledge about future fundamentals, they do not change their expectation, and consequently, they do not change their behaviors until they actually observe the change in fundamentals. In other words, the fact that expectations do not change so much over time is important for our results, regardless of where expectations come from.

To demonstrate our intuition above, we augment the baseline model with homogeneous imperfect information, i.e. agents have the same imperfect information set. For simplicity, we assume that agents observe all shocks perfectly except for the four-quarter ahead news about future permanent productivity shocks, which agents observe with a noisy signal, i.e.

$$s_t^{t+4} = \varepsilon_{x,t}^{t+4} + \eta_t. \tag{3.13}$$

Another simplifying assumption is that agents do not get any update until the shock materializes, which is when they observe the shock perfectly. We follow the solution method as in Collard et al. (2009) to solve the model. We keep the parameter values the same as the estimates of the baseline model without data on expectations. We then vary the level of noise to news shocks to show intuitively how imperfect information can alter the results. Figure 1.12 plots the impulse responses of output growth rate and its four-quarter ahead expectations to a TFP news shock happening in period 1 for different level of noises. In the first panel, we consider the case when the signal is precise and the noise is small, meaning that agents can perceive fairly accurately in period 1 that there is a news shock. In this case, output growth rate responds similarly to the perfect information case, i.e. output increases from today. Since agents can precisely perceive the news, they could forecast the movements of future output fairly well: the response of the four-period ahead expectations is the same as the response of output growth rate from period 5. In other words, this case is similar to the model with perfect information. Therefore, the role of news shocks when noise is small is similar to our baseline model where agents have perfect information.

In a setting where agents have a more noisy signal, news shocks do not generate substantial movement in expectations, causing output not to change substantially before the shock materializes. We plot in the second panel of Figure 1.12 the responses of output growth rate and its four-period ahead expectation when the standard deviation of noise is the same as the standard deviation of news. Agents in this case are not sure if there is news or not, so they put less weight on the noisy information and their four-period ahead expectations do not move as much as realized output realized in four-period. In this case, output does not change so much before agents can observe the shock, i.e. there is no strong Pigou cycle. When agents do not perceive news shock happens as the signal is very noisy as plotted in the last panel of Figure 1.12, expectations do not move much, and output growth rate does not change until the shock materializes in period 5. This case suggests that in a noisy signal setting, the fact that expectations do not move much implies that agents do not change their behaviors until they observe the shock. Therefore, the effect of news shocks in explaining short run fluctuations is negligible, and news cannot generate strong Pigou cycles. Especially in a very noisy signal situation, since agents do not change their expectations, news only matter when the shock materializes, and there is no good way to distinguish between news and unanticipated shocks. With this simple experiment, we demonstrate that news shocks are unlikely a major source of business cycles even in an imperfect information setting.

3.7 Conclusion

In this paper, we provide a new evidence about the role of news shocks in business cycles using data on expectations. This identification strategy exploits the fact that only through changes in expectations can news shocks affect agents' behaviors before actual shock materializes. We find a robust result that news shocks explain about 24% of output fluctuations in the U.S. between 1955Q1 and 2006Q4 when the model is estimated with data on expectations. This result is about half of that estimated without data on expectations. Furthermore, the precision of this estimate also improves when we use data on expectations in our estimation. The estimated contribution of news shocks to explaining short run fluctuations is even smaller, explaining about 10% of output for horizons up to two years before actual shocks materialize. These results arise because data on expectations show that changes in expectations are not large and do not resemble realized output. Therefore, news shocks cannot be main driver of business cycles when we take into account the movements of data on expectations. Additionally, our historical variance decomposition indicates that news shocks are not important in past business cycles in our sample except for the 1980 recession and 1993-94 boom, consistent with data on expectations. Our results show that data on expectations are informative about the role of news shocks in business cycles.

One implication of our analysis is that since data on expectations do not exhibit substantial movements over time, there may not be large expectation-driven business cycles. Our paper focuses on estimating a perfect information model and argues that imperfect information models are unlikely to overturn our results. Nevertheless, a future research project can formally use data on expectations to estimate models with other information structure to quantify expectation-driven business cycles.

3.8 Main Figures and Tables

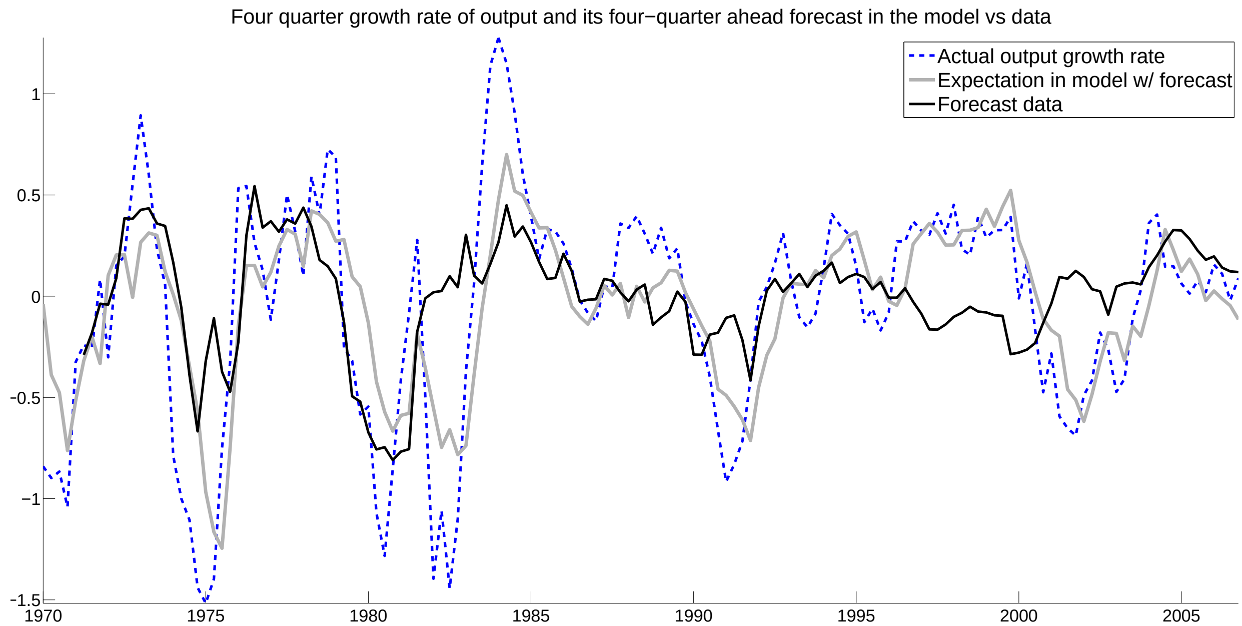


Figure 3.1: Four quarter output growth rate data with expectation implied in Schmitt-Grohe and Uribe (2012) model and forecast data. Blue dotted line is realized output growth rate, red line with plus sign is model-implied expectation 4 quarter ahead, black dashed line is four-quarter ahead data on expectations.

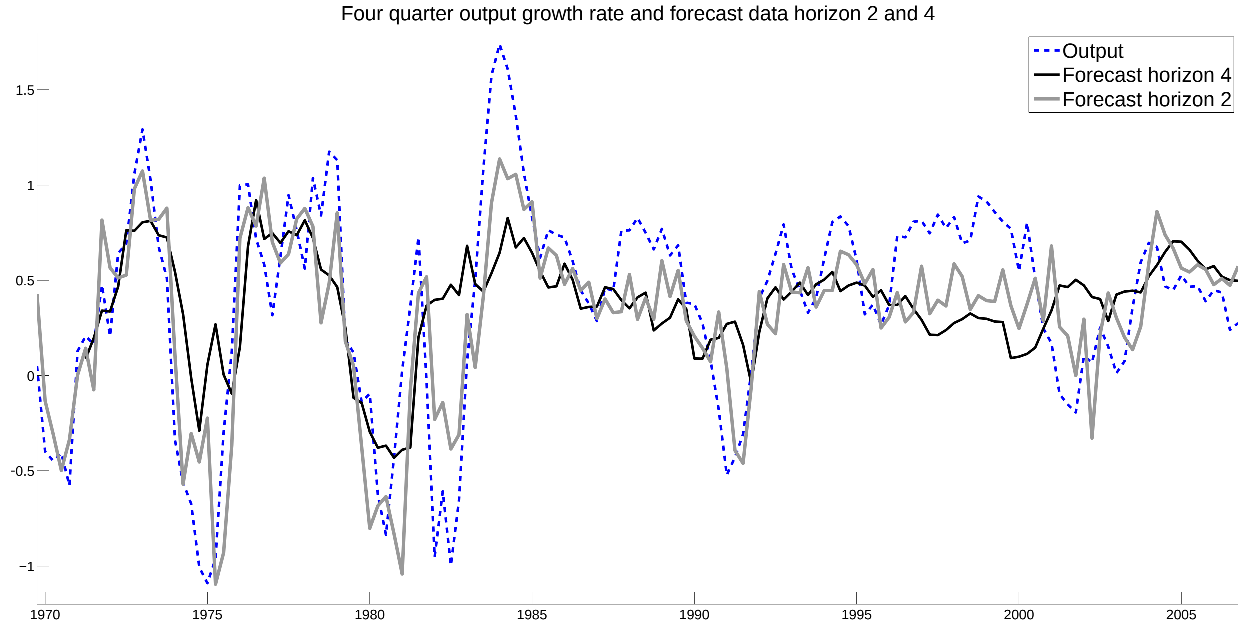


Figure 3.2: Four quarter growth rate of output: realized and data on expectations at horizon 2 and 4.

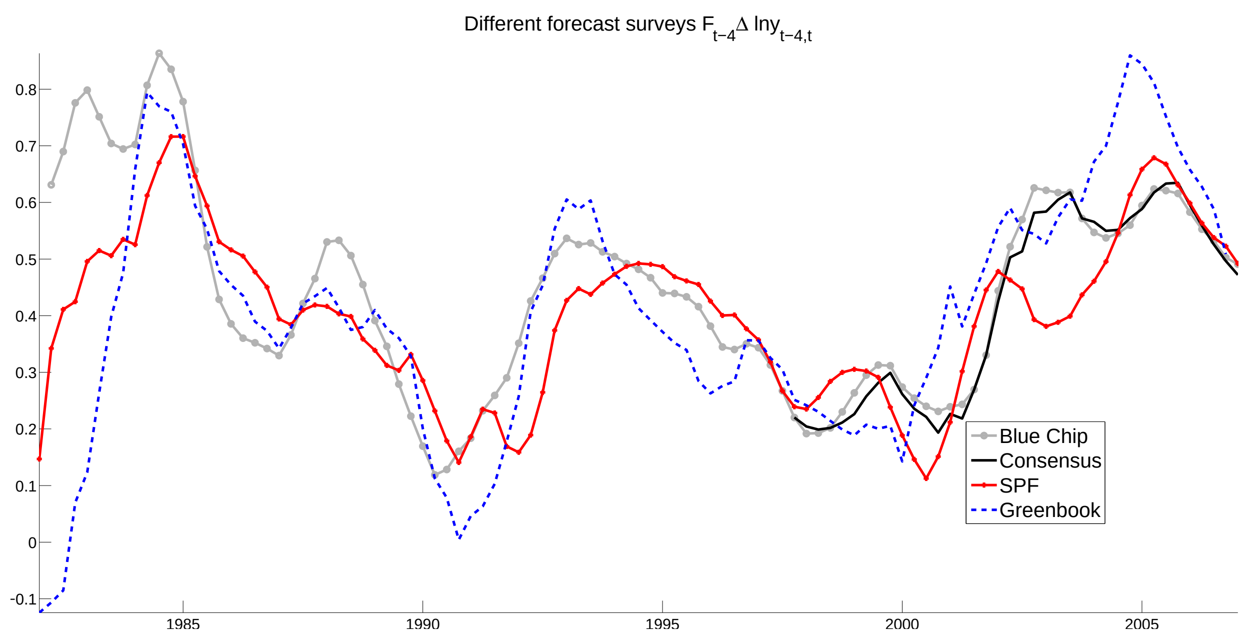


Figure 3.3: Four quarter output growth rate forecast from different surveys.

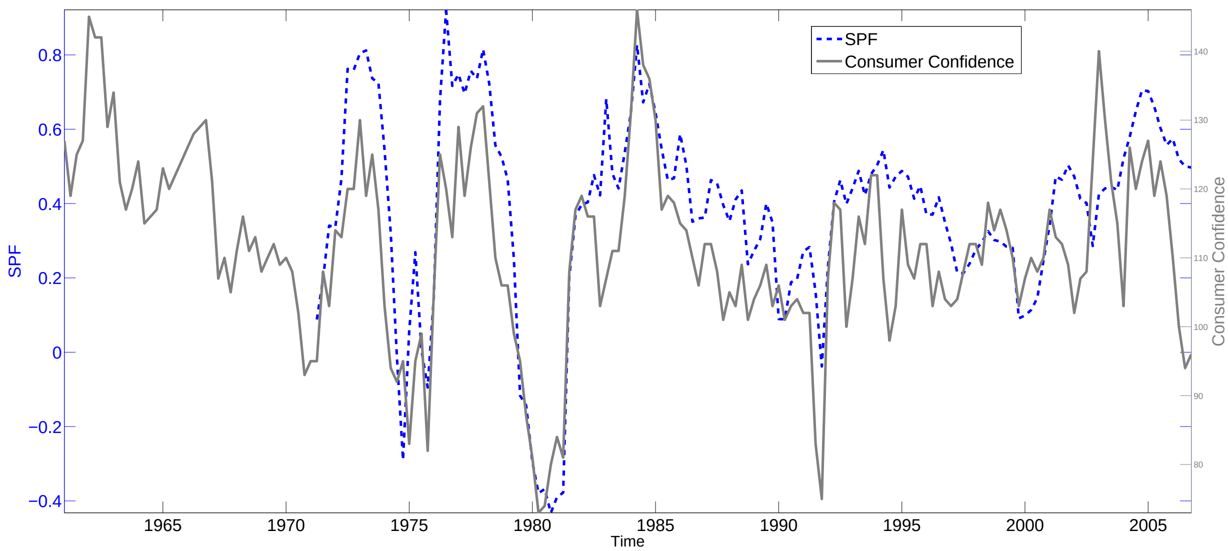


Figure 3.4: SPF four-quarter output growth rate forecast a year in advance (blue dashed line) and Expected changes in business conditions in a year from the Michigan survey of Consumer Confidence (gray line).

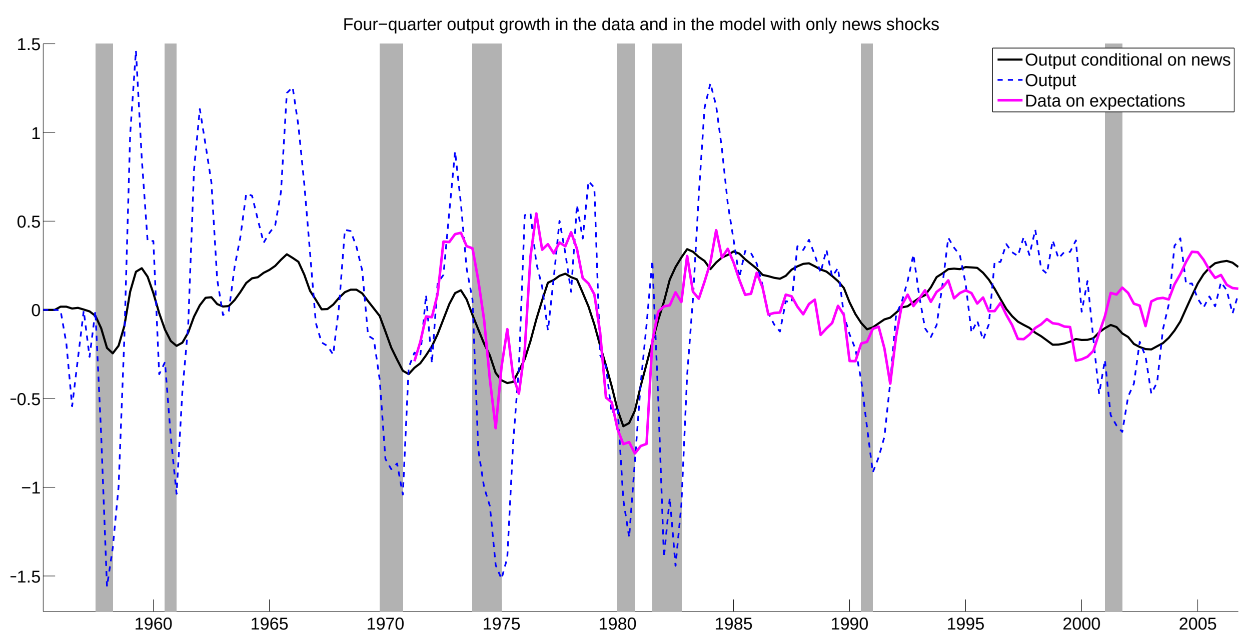


Figure 3.5: Four quarter output growth rate in the data (the dashed blue line) and in the model with only news shocks (the black line) and forecast data (the pink line).

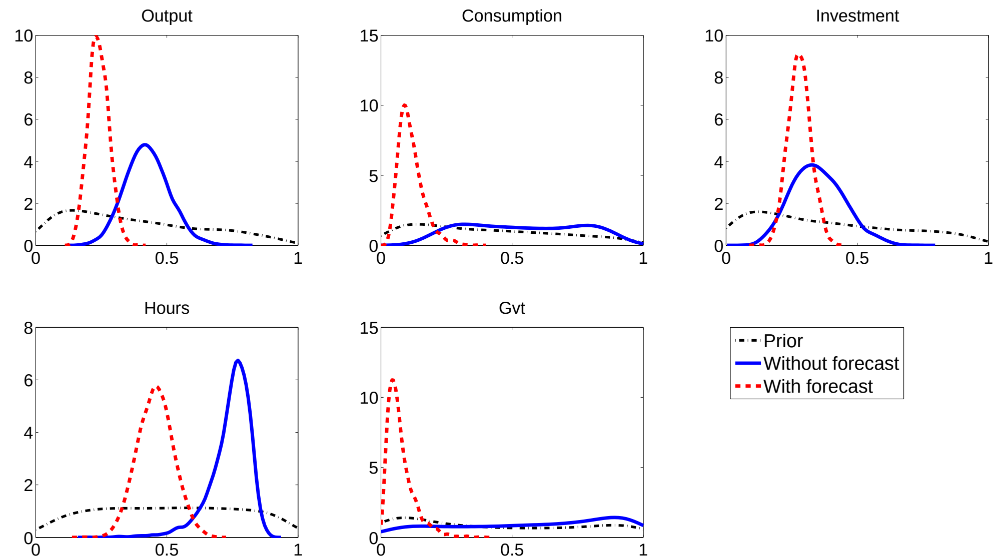


Figure 3.6: Posterior distribution of the shares of the variances of output, consumption, investment, hours and government spending growth rates due to news with and without forecast.

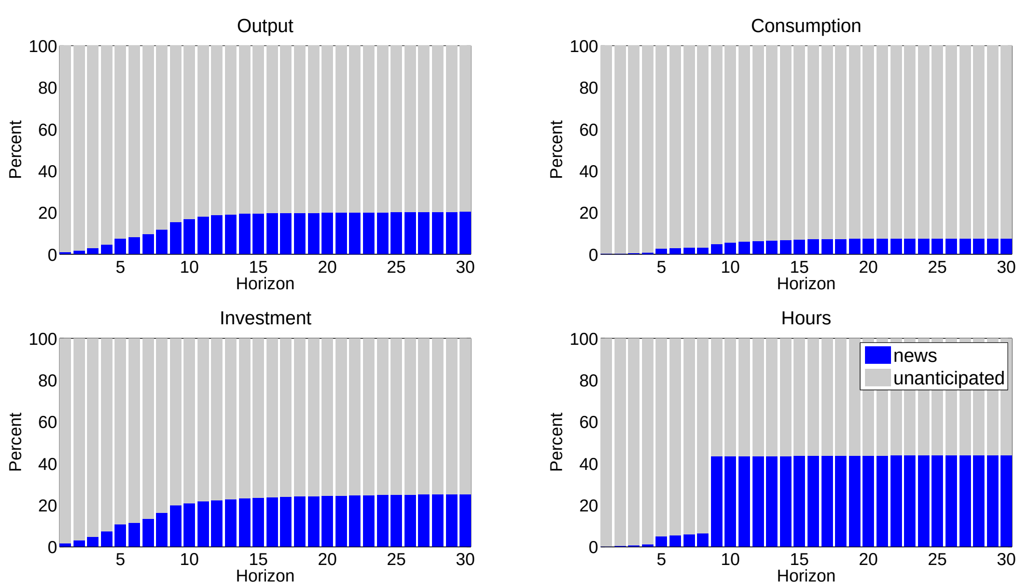


Figure 3.7: Forecast error variance decomposition

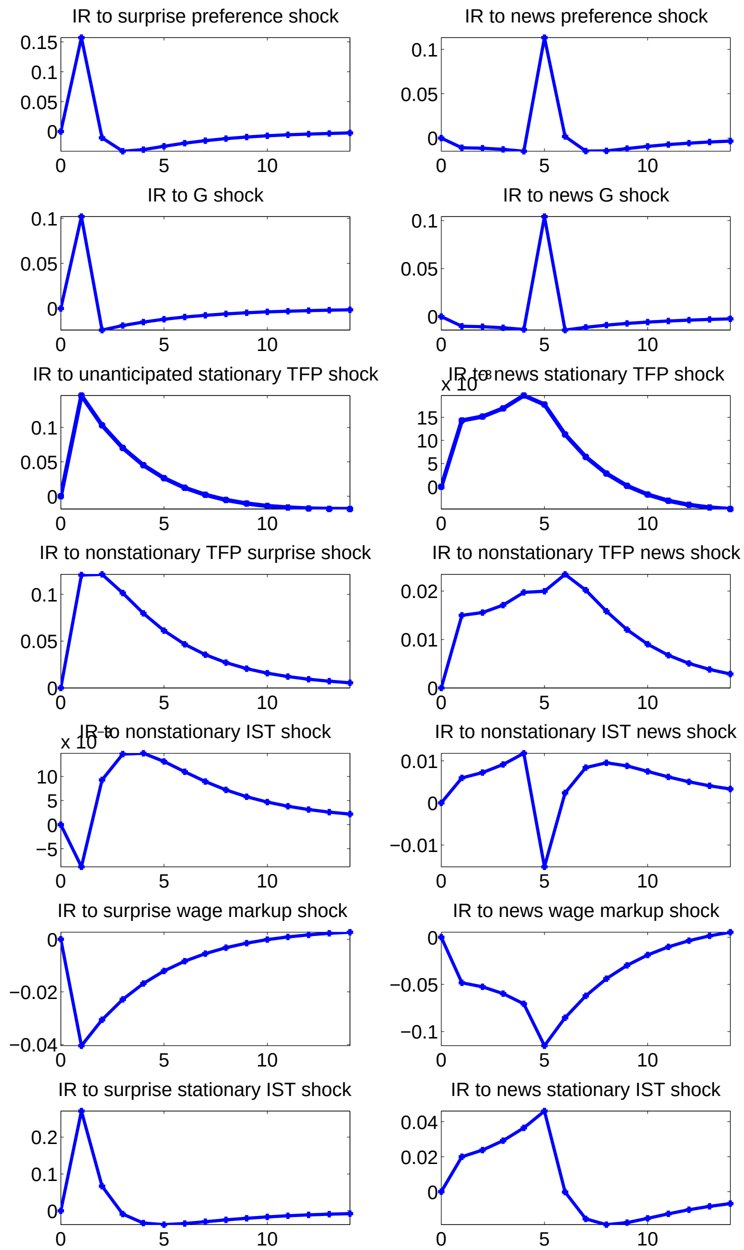


Figure 3.8: Impulse responses of output growth rate $\Delta \ln y_t$ to unanticipated and 4-period ahead news shocks.

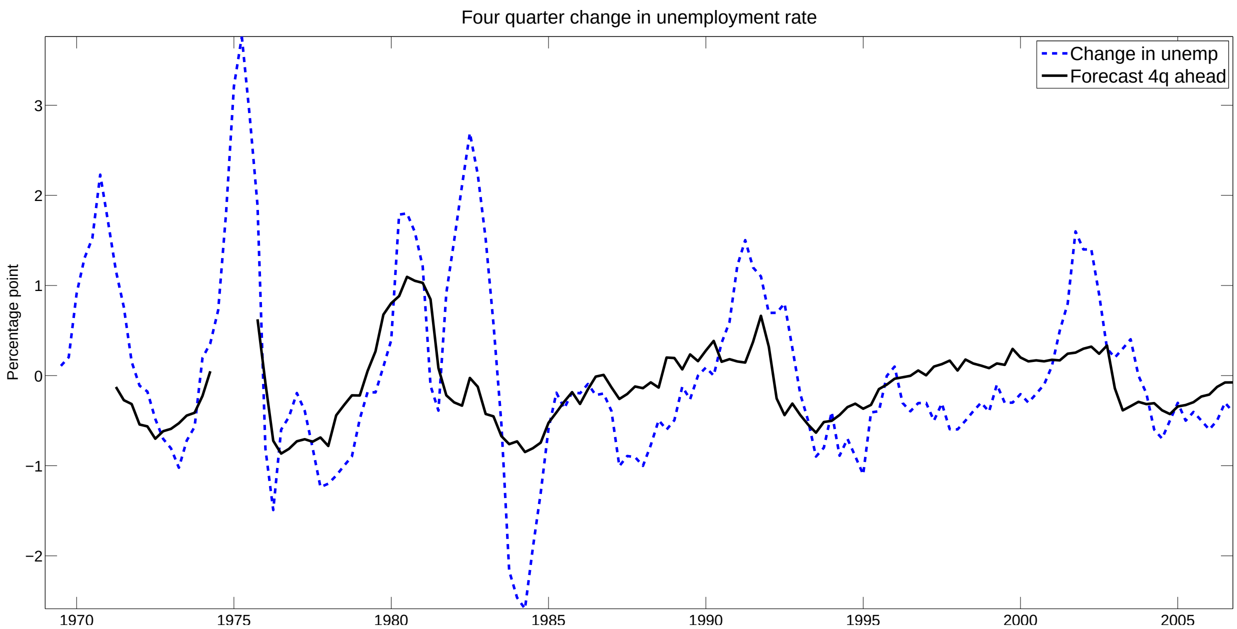


Figure 3.9: Realized unemployment rate change and the corresponding four-quarter ahead forecast.

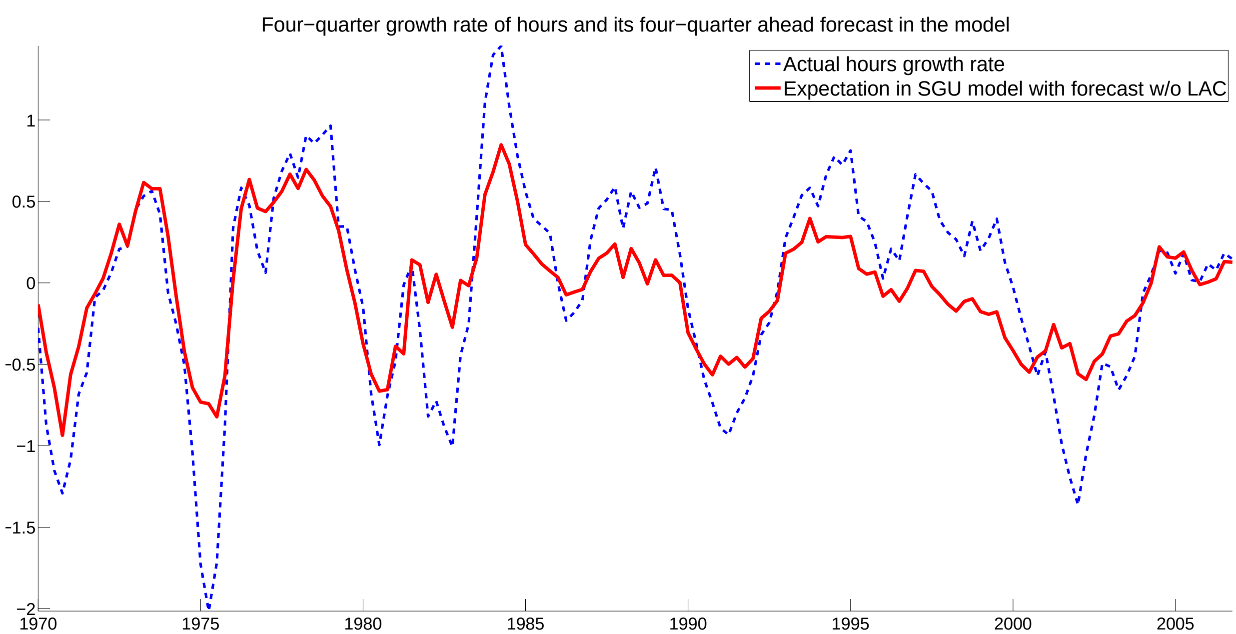


Figure 3.10: Four-quarter hours growth rate and the four-quarter ahead expectation implied by the SGU model estimated with output forecast. The model-implied expectations are calculated using the median of the posterior distribution of the parameters.

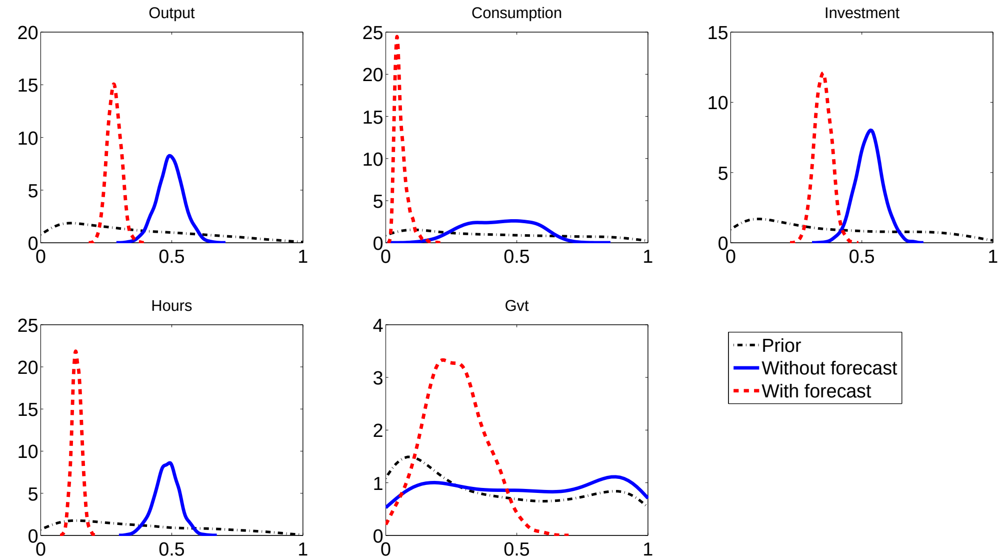


Figure 3.11: Posterior distribution of the shares of the variances of output, consumption, investment, hours and government spending growth rates due to news with and without forecast in the model with nominal rigidities.

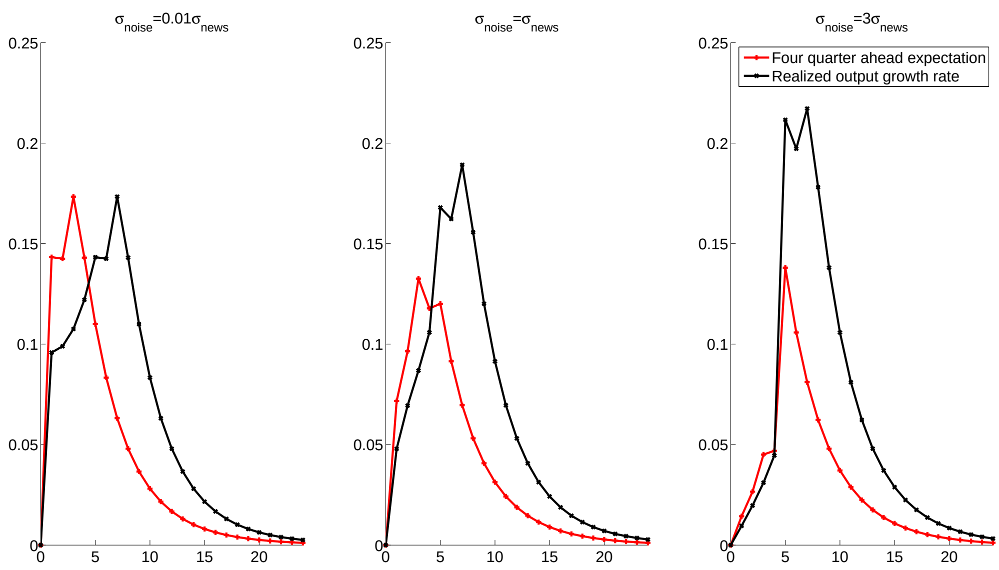


Figure 3.12: Impulse responses of output growth rate and four-quarter ahead expectations to a four-quarter ahead TFP news shock received with different level of noises.

	Nowcast	Horizon 1	Horizon 2	Horizon 3	Horizon 4
Standard deviation: $\sigma_{forecast}/\sigma_{realized}$					
$\Delta \ln y_{t-1,t}$	0.56	0.38	0.29	0.25	0.25
$\Delta \ln c_{t-1,t}$	0.51	0.33	0.25	0.23	0.21
$\Delta \ln I_{t-1,t}$	0.59	0.39	0.27	0.23	0.22
Correlation with Output growth rate					
$\Delta \ln y_{t-1,t}$	0.71	0.46	0.33	0.12	0.08
$\Delta \ln c_{t-1,t}$	0.60	0.41	0.22	-0.06	-0.01
$\Delta \ln I_{t-1,t}$	0.59	0.44	0.30	0.11	0.03
Autocorrelation					
$\Delta \ln y_{t-1,t}$	0.67	0.67	0.69	0.74	0.75
$\Delta \ln c_{t-1,t}$	0.54	0.68	0.63	0.53	0.71
$\Delta \ln I_{t-1,t}$	0.82	0.80	0.78	0.77	0.76
Mean forecast errors (in percent)					
$\Delta \ln y_{t-1,t}$	0.16*	0.08	0.03	-0.02	-0.01
Persistence of forecast errors: $\Delta \ln y_{t-1,t} - F_{t-k} \Delta \ln y_{t-1,t} = \alpha + \beta \left(\Delta \ln y_{t-k-1,t-k} - F_{t-k-k} \Delta \ln y_{t-k-1,t-k} \right)$					
α		0.09	0.04	0.00	0.00
β		0.10	0.10	0.04	0.06

Table 3.1: Second moments of SPF data for quarterly output, consumption and investment growth rates between 1970Q4 and 2010Q4. $\Delta \ln y_{t-1,t}, \Delta \ln c_{t-1,t}, \Delta \ln I_{t-1,t}$ *denote growth rates between time* $t-1$ *and time* t *of output, consumption and investment, respectively.* F_{t-k} *denotes the forecast made at time* $t-k$*.*
Note: a star next to the autocorrelation of forecast errors, mean and the regression coefficient means it is significant at at least 10% confidence level.

	Parameter	Value
δ_0	depreciation rate	0.025
β	discount factor	0.99
α_k	capital share	0.225
α_h	labor share	0.675
h	steady state hours	0.2
gss	steady state share of government spending in output	0.2
μ_{zi}	steady state gross growth rate of price of investment	1.01
μ_y	steady state gross per capital GDP growth rate	1.0045
η_{wss}	steady state wage markup	1.15

Table 3.2: Calibrated parameters

Parameters	Priors			Posterior without forecast			Posterior with forecast		
	Distribution	Mean	Std	median	5%	95%	median	5%	95%
v	G	4	1	4.11	3.21	5.16	4.79	3.74	6.05
γ	U	0.5	0.29	0.00	0.00	0.01	0.00	0.00	0.00
δ_2/δ_1	IG	1	1	0.36	0.24	0.52	0.39	0.25	0.56
s	G	4	1	9.22	7.41	11.34	8.84	7.10	10.89
κ	B	0.5	0.2	0.90	0.87	0.92	0.94	0.92	0.96
$\rho_{\mu_{zn}}$	B	0.7	0.2	0.86	0.61	0.98	0.95	0.83	0.99
$\rho_{\mu_{zi}}$	B	0.5	0.2	0.48	0.39	0.58	0.48	0.38	0.57
ρ_{an}	B	0.7	0.2	0.92	0.84	0.96	0.75	0.64	0.85
ρ_{ai}	B	0.5	0.2	0.43	0.20	0.63	0.42	0.32	0.51
ρ_g	B	0.7	0.2	0.96	0.93	0.99	0.97	0.95	0.99
ρ_b	B	0.5	0.2	0.18	0.08	0.31	0.36	0.27	0.46
ρ_{η_w}	B	0.7	0.2	0.98	0.95	1.00	0.96	0.93	0.98
ρ_{xg}	B	0.7	0.2	0.73	0.44	0.89	0.66	0.37	0.85
$\sigma^0_{\mu_{zn}}$	G	0.45	0.45	0.38	0.19	0.56	0.33	0.26	0.42
$\sigma^0_{\mu_{zi}}$	G	0.31	0.31	0.20	0.03	0.34	0.25	0.05	0.35
σ_{a^n}	G	1.5	1.5	0.65	0.53	0.74	0.64	0.52	0.73
σ_{a^i}	G	17.15	17.15	12.10	8.94	15.86	12.86	9.97	16.51
σ_g	G	1.05	1.05	0.66	0.09	1.07	1.07	0.97	1.18
σ_b	G	6.3	6.3	3.95	0.73	6.54	11.30	7.28	18.00
σ_{η_w}	G	1.19	1.19	0.84	0.10	2.58	3.58	2.60	4.67
$\sigma^4_{\mu_{zn}}$	G	0.19	0.19	0.09	0.01	0.28	0.10	0.01	0.26
$\sigma^8_{\mu_{zn}}$	G	0.19	0.19	0.11	0.01	0.29	0.20	0.04	0.35
$\sigma^4_{\mu_{zi}}$	G	0.13	0.13	0.16	0.02	0.34	0.08	0.01	0.24
$\sigma^8_{\mu_{zi}}$	G	0.13	0.13	0.17	0.02	0.34	0.21	0.02	0.34
σ^4_{an}	G	0.61	0.61	0.12	0.02	0.33	0.13	0.02	0.32
σ^8_{an}	G	0.61	0.61	0.11	0.01	0.30	0.15	0.02	0.41
σ^4_{ai}	G	7	7	2.55	0.30	7.39	4.83	1.78	7.38
σ^8_{ai}	G	7	7	5.70	1.12	10.75	4.32	1.02	6.80
σ^4_{gvt}	G	0.43	0.43	0.59	0.06	1.06	0.14	0.02	0.40
σ^8_{gvt}	G	0.43	0.43	0.35	0.04	0.96	0.11	0.01	0.31
$\sigma^4_{\eta_w}$	G	0.49	0.49	4.74	0.31	5.81	0.45	0.04	1.73
$\sigma^8_{\eta_w}$	G	0.49	0.49	0.73	0.06	5.16	4.58	3.67	5.56
σ^4_b	G	2.57	2.57	2.14	0.23	5.75	1.58	0.19	4.24
σ^8_b	G	2.57	2.57	2.16	0.22	5.92	1.10	0.13	3.16
me^y	U	0.14	0.08	0.29	0.29	0.29	0.29	0.29	0.29
me^{y2}	U	0.06	0.03				0.11	0.10	0.12
me^{y4}	U	0.04	0.02				0.01	0.00	0.03

Table 3.3: Estimated Parameters. Note: The estimated parameters are reported at posterior mean of the distribution computed from the last 200,000 draws.

	$\Delta \ln y_{t-1,t}$	$\Delta \ln c_{t-1,t}$	$\Delta \ln I_{t-1,t}$	$\Delta \ln h_{t-1,t}$	$\Delta \ln G_{t-1,t}$
Standard deviation					
Data	0.91	0.51	2.28	0.84	1.15
W/o forecast	0.65	0.75	2.67	0.83	1.13
W/ forecast	0.63	0.58	2.75	0.88	1.15
W/ LAC w/ forecast	0.64	0.61	2.78	0.76	1.13
Correlation with $\Delta \ln y_{t-1,t}$					
Data	1.00	0.50	0.69	0.72	0.25
W/o forecast	1.00	0.63	0.76	0.45	0.36
W/ forecast	1.00	0.55	0.72	0.43	0.38
W/ LAC w/ forecast	1.00	0.56	0.71	0.50	0.37
Autocorrelation					
Data	0.28	0.20	0.52	0.59	0.05
W/o forecast	0.49	0.37	0.59	0.13	0.02
W/ forecast	0.49	0.43	0.56	0.06	0.03
W/ LAC w/ forecast	0.48	0.35	0.57	0.44	0.04

Table 3.4: Model Fit: second moments. Each panel displays the second moments (standard deviation, correlation with output growth rate, and autocorrelation) of output ($\Delta \ln y_{t-1,t}$), consumption ($\Delta \ln c_{t-1,t}$, investment ($\Delta \ln I_{t-1,t}$), hours ($\Delta \ln h_{t-1,t}$) and government spending ($\Delta \ln G_{t-1,t}$) in the data ("Data"), and the corresponding second moments implied in the estimated model without data on expectations ("W/o forecast"), in the estimated model with data on expectations ("W/ forecast"), and in the model with labor adjustment cost estimated with data on expectations ("W/ LAC w/ forecast").

Variable	Without forecast	With forecast	With forecast
	Baseline model		W/ Labor adj
$\Delta \ln y_{t-1,t}$	42.2	24.2	24.7
	(29.3, 56.7)	(18.4, 30.5)	(17.8, 31.6)
$\Delta \ln c_{t-1,t}$	53.1	11.1	8.3
	(21.8, 87.3)	(5.80, 20.4)	(3.5, 15.4)
$\Delta \ln I_{t-1,t}$	34.3	28.2	30.9
	(19.6, 52.0)	(21.7, 34.9)	(23.1, 38.7)
$\Delta \ln h_{t-1,t}$	75.8	46.1	33.6
	(59.8, 83.5)	(35.3, 57.6)	(12.2, 50.8)
$\Delta \ln G_{t-1,t}$	57.3	7.7	7.0
	(6.69, 96.0)	(1.96, 18.3)	(1.6, 17.1)

Table 3.5: Contribution of all news shocks. The contribution is reported at posterior mean of the distribution, computed from 200,000 draws. The numbers in parentheses are the $5-95\%$ confidence interval.

Innovation	Without forecast					With forecast				
	$\Delta \ln y_{t-1,t}$	$\Delta \ln c_{t-1,t}$	$\Delta \ln I_{t-1,t}$	$\Delta \ln h_{t-1,t}$	$\Delta \ln G_{t-1,t}$	$\Delta \ln y_{t-1,t}$	$\Delta \ln c_{t-1,t}$	$\Delta \ln I_{t-1,t}$	$\Delta \ln h_{t-1,t}$	$\Delta \ln G_{t-1,t}$
Nonstationary TFP										
pd 0	13.40	8.37	6.62	1.80	3.65	13.35	5.50	7.88	1.23	3.95
pd 4	1.17	0.91	0.43	0.55	0.50	1.48	0.79	0.66	0.44	0.66
pd 8	1.15	0.86	0.47	0.66	0.64	3.04	1.65	1.34	1.10	1.63
Nonstationary IST										
pd 0	0.34	0.08	0.39	0.22	0.14	0.51	0.09	0.48	0.26	0.21
pd 4	0.32	0.07	0.43	0.12	0.12	0.12	0.02	0.14	0.04	0.05
pd 8	0.29	0.09	0.46	0.11	0.12	0.41	0.07	0.51	0.14	0.17
Government spending										
pd 0	3.47	0.18	0.37	0.72	38.92	8.81	0.36	1.10	1.59	88.10
pd 4	3.67	0.22	0.19	0.94	35.39	0.37	0.01	0.02	0.07	3.21
pd 8	2.13	0.11	0.09	0.55	20.51	0.23	0.01	0.01	0.05	2.02
Preference										
pd 0	7.51	32.35	0.98	2.02	0.00	16.87	78.65	5.14	4.16	0.00
pd 4	4.38	16.88	0.33	1.37	0.00	0.76	2.83	0.11	0.19	0.00
pd 8	4.57	17.66	0.28	1.41	0.00	0.43	1.60	0.05	0.11	0.00
Wage markup										
pd 0	1.42	1.19	0.93	5.16	0.00	6.93	2.89	6.48	26.85	0.00
pd 4	12.57	12.51	8.79	50.81	0.00	0.27	0.14	0.27	1.19	0.00
pd 8	2.78	3.07	1.82	12.77	0.00	7.43	4.34	7.15	37.59	0.00
Stationary TFP										
pd 0	11.01	2.93	13.32	12.87	0.00	3.47	0.13	5.91	16.49	0.00
pd 4	0.70	0.29	0.70	1.49	0.00	0.30	0.03	0.42	1.41	0.00
pd 8	0.45	0.19	0.45	1.20	0.00	0.43	0.05	0.58	2.06	0.00
Stationary IST										
pd 0	20.36	0.75	42.45	2.98	0.00	25.74	0.51	44.74	3.30	0.00
pd 4	2.33	0.24	5.61	0.58	0.00	5.01	0.15	9.39	0.93	0.00
pd 8	6.00	1.03	14.87	1.67	0.00	4.05	0.19	7.62	0.83	0.00

Table 3.6: Variance decomposition of model estimated without and with forecast

Variable	With forecast 1970Q1-2006Q1	With real time data 1955Q1-2006Q4	With 4Q ahead 1955Q1-2006Q4	With 1-4Q ahead 1955Q1-2006Q4	With all forecast 1955Q1-2006Q4	With sticky price 1955Q1-2006Q4
$\Delta \ln y_{t-1,t}$	26.6	17.30	26.2	24.10	20.00	28.00
	(19.8, 34.3)	(12.9, 22.1)	(18.8, 34.3)	(19, 29)	(16.7, 23.5)	(23.8, 32.2)
$\Delta \ln c_{t-1,t}$	15.7	4.50	17.8	5.40	9.07	5.72
	(4.69, 31.2)	(1.55, 9.50)	(8.9, 31.4)	(2.83, 8.78)	(6.75, 11.9)	(3.9, 10.5)
$\Delta \ln I_{t-1,t}$	29.5	28.14	24.8	31.80	26.05	35.19
	(21.9, 38.5)	(20.9, 35.7)	(16.3, 33.5)	(25.9, 37.9)	(21.0, 31.7)	(30, 40)
$\Delta \ln h_{t-1,t}$	40.4	44.82	51.9	46.90	62.30	13.78
	(14.5, 64.7)	(12.2, 66.1)	(40.7, 62.8)	(35, 58)	(46.9, 72.7)	(11, 16.7)
$\Delta \ln G_{t-1,t}$	12.2	8.10	11.60	4.40	3.80	26.10
	(2.96, 29.0)	(1.98, 18.0)	(2.88, 29.1)	(1.22, 8.6)	(2.24, 5.70)	(8.4, 45.1)

Table 3.7: Contribution of news shocks: Robustness (1) with different period, (2) with real time realized data, (3) using only four-quarter ahead expectations of output, (4) using one-, two-, three- and four-quarter ahead expectations, and (5) all data on expectations of output, consumption, investment and government spending as observables, (6) in model with sticky price

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Appendices

Appendix A

Appendix for Chapter 1

A.1 Data Source

The data are compiled from many sources but primarily, as written in the paper, from Barro and Ursúa (2009) dataset for GDP per capita and consumption per capita. All population data are taken from Maddison (2009). All terms of trade data are taken from Oxford Latin American Economic History Database (OxLad), International Financial Statistics (IFS), World Development Indicators (WDI) and the historical data sources listed below.

1. **Argentina**: Updated the dataset given by Garcia-Cicco, Pancrazi and Uribe (2010) available at `http://www.columbia.edu/\char126\relaxmu2166/rbc_emerging/rbc_emerging.html`

   2006 data are from Secretearia de Politica Economica (2006). Available at `http://www.mecon.gov.ar/peconomica/informe/indice.htm` and `http://www.indec.gov.ar/principal.asp?id_tema=165`

2. **Australia**: GDP and Consumption per capita are taken from Barro and Ursúa (2009)

available at http://www.economics.harvard.edu/faculty/barro/data_sets_barro

Investment and Trade balance:

1901-1959: Vamplew, Wray (ed.), Australians, historical statistics, Fairfax, Syme & Weldon, Australia, 1987.

1960-2006: Central bank Statistics available at http://abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5206.0Dec%202009?OpenDocument

3. **Brazil**: GDP and Consumption per capita are taken from Barro and Ursua (2009) as above

   Investment and Trade balance:

   1900-2000: OxLad available at http://oxlad.qeh.ox.ac.uk/search.php

   2001-2007: IFS available at http://www.imfstatistics.org/IMF/imfbrowser.aspx?branch=ROOT

   IPPEA available at http://www.ipeadata.gov.br/ipeaweb.dll/ipeadata?Tick=1356034625 and Estatísticas Econômicas available at http://www.ibge.gov.br/seculoxx/economia/contas_nacionais/contas_nacionais.shtm

4. **Canada**: GDP and Consumption per capita are taken from Barro and Ursúa (2009) as above

   Investment and Trade balance:

   1900-1925: Urquhart, M.C., Gross National Product, Canada, 1870-1926: The Derivation of the Estimates, McGill-Queen's University Press, Canada, 1993

   1926-1960: Historical Statistics of Canada, 2nd edition. 1983, available at http://www.statcan.gc.ca/pub/11-516-x/11-516-x1983001-eng.htm

1961-2006: Statistics Canada, National Income and Expenditure Accounts [Table 380-0017: Gross Domestic Product (GDP), expenditure-based]. Available at: http://cansim2.statcan.ca/

5. **Chile**: GDP and Consumption per capita are taken from Barro and Ursúa (2009) as above

   Investment and Trade balance:

   1900-1980: OxLad as above

   1981-2006: IFS as above

   Braun, Juan, Matías Braun, Ignacio Briones, and José Díaz, "Economía Chilena 1810-1995: Estadísticas Históricas", Instituto de Economía - Pontifica Universidad Católica de Chile, Documento de Trabajo No. 187, January, 2000.

6. **Colombia**: All data are taken from Fernández, Andrés. "Tropical" Real Business Cycles? A Bayesian Exploration (2009). Mimeo, Rutgers University, and Banco de la República Colombia, at http://www.banrep.gov.co/series-estadisticas/see_prod_salar.htm

7. **Finland**: GDP and Consumption per capita are taken from Barro and Ursúa (2009) as above

   Investment and Trade balance:

   1900-1975: Hjerppe, Riitta, The Finnish Economy 1860-1985: Growth and Structural Change, Bank of Finland Publications, Studies on Finland's Economic Growth XIII, Helsinki, 1989.

   1975-2006: Statistics Finland, available at http://pxweb2.stat.fi/database/StatFin/kan/pka/pka_en.asp

8. **India**: GDP and Consumption per capita are taken from Barro and Ursúa (2009) as above

   Investment and Trade balance:

   1919-1950: Narasinham, N. V. A., A Short Term Planning Model for India, North Holland Publishing Company, Amsterdam, 1956.

   1951-2006: Central Statistical Office, Government of India, "National Accounts tables", available at http://mospi.nic.in/mospi_nad_main.htm

9. **Mexico**: I updated the dataset given by Garcia-Cicco, Pancrazi and Uribe (2010). 2006 data are from Instituto Nacional de Estadiistica, Geografiia e Informatica (INEGI), available at http://dgcnesyp.inegi.org.mx/bdiesi/bdie.html

10. **Norway**: All data are taken from:

    1830-1969: Grytten, Ola, "The gross domestic product for Norway 1830–2003", in: Øyvind Eitrheim, Jan T. Klovland and Jan F. Qvigstad (eds.), Historical monetary statistics for Norway, 2005. Available at the Nordic Historical National Accounts Database,(courtesy of Prof Guomundur Jonsson), available at http://old.nhh.no/forskning/nnb/

    1941-1945: Ola Grytten kindly provided me with his estimates

    1970-2006: Central Bank of Norway, "National accounts", available at http://www.ssb.no/english/subjects/09/01/nr_en/

11. **Peru**: GDP and Consumption per capita are taken from Barro and Ursúa (2009) as above. All other data are from courtesy of Bruno Seminario, available at http://sites.google.com/site/lbseminario/peru-2021

12. **Portugal**: GDP and Consumption per capita are taken from Barro and Ursúa (2009) as above. All other data are taken from:

    Batista, Dina; Martins, Carlos; Pinheiro, Maximiano and Reis, Jaime, New Estimates for Portugal's GDP (1910-1958), Lisboa, 1997. Available at Professor Pedro Lain's personal website `http://pedrolains.typepad.com/pedrolains/estatsticas-data.html`

13. **Spain**: GDP and Consumption per capita are taken from Barro and Ursúa (2009) as above. Additionally, data are taken from

    1900-1994: Prados de la Escosura, Leandro, El progreso económico de España, 1850-2000, Fundacion BBVA, Madrid, 2003

    1995-2006: Instituto Nacional de Estadística, Contabilidad Nacional de España, Producto interior bruto a precios de mercado y sus componentes `http://www.ine.es/jaxi/menu.do?L=1&type=pcaxis&path=%2Ft35%2Fp008&file=inebase&N=&L=`

14. **Sweden**: GDP and Consumption per capita are taken from Barro and Ursúa (2009) as above.

    Investment and Trade balance:

    Edvinsson, Rodney, Historical national accounts for Sweden 1800-2000 (Historiska-nationalräkenskaper för Sverige 1800-2000). Based on:Edvinsson, R., 2005: Growth, Accumulation, Crisis: With New Macroeconomic Data for Sweden. Almqvist & Wiksell International; Stockholm.

    1900-1992: the Nordic Historical National Accounts Database, available at `http://old.nhh.no/forskning/nnb/`

    1993-2006: Statistics Sweden, Economic statistics available at `http://www.scb.se/Pages/List____258713.aspx`

15. **Taiwan**: GDP and Consumption per capita are taken from Barro and Ursúa (2009) as above.

    Investment and Trade balance:

    1901-1950: National Historical data

    Mizoguchi, Toshiyuki, "Estimates of the Long-run Economic Growth of Taiwan Based on Revised SNA (1901-2000) Statistics", Institute for Economic Research - Hitotsubashi University, Discussion Paper Series, No. 123, October, 2005.

    1951-2006: National statistics, available at `http://eng.stat.gov.tw/mp.asp?mp=5`

16. **Turkey**: GDP and Consumption per capita are taken from Barro and Ursúa (2009) as above.

    Investment and Trade balance:

    Altug, Sumru, Alpay Filitztekin and Sevket Pamuk. "Sources of long-term economic growth for Turkey, 1880-2005". European Review of Economic History, 12(3) pp.393-430, December 2008. Available at `http://myweb.sabanciuniv.edu/alpayf/my-research/data/`

    Turkish Statistical Institute. Foreign Trade table, available at `http://www.turkstat.gov.tr/PreTablo.do?tb_id=12&ust_id=4`

    State Institute of Statistics (Devlet İstatistik Enstitüsü), Statistical indicators (İstatistik göstergeler): 1923-2008, Ankara, Turkey, 2009, available at `http://www.tuik.gov.tr/Kitap.do?metod=KitapDetay&KT_ID=0&KITAP_ID=158`

17. **Venezuela**: Besides data taken from Barro and Ursúa (2009) as above, I also constructed GDP, Consumption per capita and the other series from:

1920-2002: Baptista, Asdrúbal, Bases Cuantitativas de la Economía Venezolana: 1830-2002, Fundación Polar, Caracas, Venezuela, 2006

1998-2006: Central bank of Venezuela: Banco Central De Venezuela, available at `http://www.bcv.org.ve/c2/indicadores.asp`

Appendix B

Appendix for Chapter 2

B.1 Non-fuel Terms of trade

Following Baxter and Crucini (2000), we can decompose the terms of trade as followed:

$$\left(\frac{P_t^F}{P_t^D}\right)_{nf} = \frac{P_t^F}{P_t^D}\left(\frac{S^F}{S^D}\right)_{nf}\frac{Q^F}{Q^D}$$

where nf denotes non-fuel, S^i is the share of non-fuel export (import) in total export (import) in current prices, Q^F is the ratio of the quantity of non-fuel imports to the quantity of total trade valued at base year. Assume $Q^F = Q^D$, we calculate the non-fuel terms of trade.

B.2 Additional Evidence of Transmission: Mexico

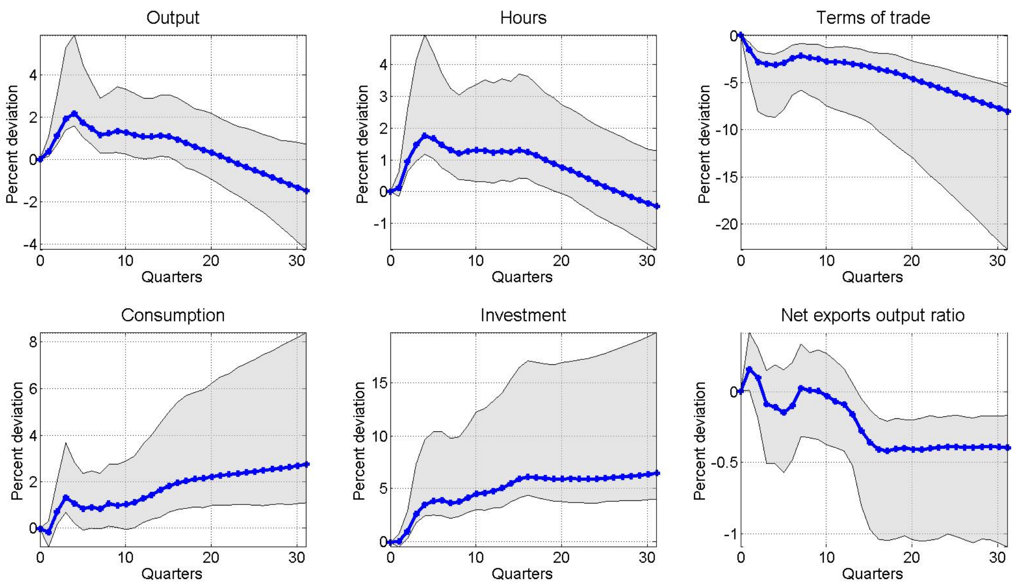

Figure B.1: The responses of Mexico to a positive U.S. permanent technology shocks using Mexican manufacturing data between 1980Q1 and 2011Q3. Lines with plus sign is the point estimate and the shaded areas are the 95% *confidence intervals.*

Appendix C

Appendix for Chapter 3

C.1 Data Appendix

- Population: smooth out LNU00000000Q
- Real GDP (from NIPA 1.1.6): Real GDP/Population
- Investment: Nominal fixed investment/Population/GDP deflator
- Consumption: Nominal consumption/Population/GDP deflator
- Hours: PRS85006023*Employment (LNS12000000) /100/Population

  OR PRS85006033/Population
- Wage: nominal wage (PRS85006103)/GDP deflator
- Government spending: Nominal Government spending/Population/GDP deflator
- Interest rate: Tbill from FRB_H15
- Relative investment prices: Fixed investment price deflator/GDP deflator

C.2 Baseline Model Equilibrium Conditions

Stationary FOC:

$$n_t = \left(c_t - \kappa \frac{c_{t-1}}{\mu_t}\right)^{\gamma} \frac{n_{t-1}^{1-\gamma}}{\mu_t^{1-\gamma}} \tag{C.1}$$

$$v_t = c_t - \kappa \frac{c_{t-1}}{\mu_t} - \psi h_t^{\nu} n_t \tag{C.2}$$

$$b_t v_t^{-\sigma} - \beta\kappa E_t b_{t+1} \frac{1}{\mu_{t+1}^{\sigma}} v_{t+1}^{-\sigma} - \lambda_{3t}\gamma \frac{n_t}{c_t - \kappa \frac{c_{t-1}}{\mu_t}} + \beta\kappa\gamma E_t \frac{1}{\mu_{t+1}^{\sigma}} \lambda_{3t+1} \frac{n_{t+1}}{c_{t+1} - \frac{\kappa c_t}{\mu_{t+1}}} = \lambda_{1t} \tag{C.3}$$

$$-b_t v_t^{-\sigma} \psi \nu h_t^{\nu-1} n_t + \lambda_{1t} w_t^h = 0 \tag{C.4}$$

$$-b_t \psi v_t^{-\sigma} h_t^{\nu} + \lambda_{3t} - (1-\gamma)\beta E_t \frac{1}{\mu_{t+1}^{\sigma}} \lambda_{3t+1} \frac{\mu_{t+1} n_{t+1}}{n_t} = 0 \tag{C.5}$$

$$\lambda_{1,t} \frac{1}{R_t} = \beta \lambda_{1,t+1} \mu_{t+1}^{-\sigma} \tag{C.6}$$

$$\lambda_{2,t} = \beta E_t \left[\lambda_{1,t+1} \mu_{t+1}^{-\sigma} \frac{z_t^i}{z_{t+1}^i} r_{t+1}^k u_{t+1} + \lambda_{2,t+1} \mu_{t+1}^{-\sigma} \frac{z_t^i}{z_{t+1}^i} \left(1 - \delta\left(u_{t+1}\right)\right)\right] \tag{C.7}$$

$$\lambda_{1t} r_t^k = \lambda_{2t} \left(\delta_1 + \delta_2 \left(u_t - 1\right)\right) \tag{C.8}$$

$$\lambda_{1,t} = \lambda_{2,t} \left[a_t^i \left(1 - \frac{s}{2}\left(\mu_t^i \frac{i_t}{i_{t-1}} - \mu_I\right)^2\right) - s a_t^i \frac{i_t}{i_{t-1}} \mu_t^i \left(\frac{i_t}{i_{t-1}} \mu_t^i - \mu_I\right)\right] \tag{C.9}$$

$$+\beta E_t \lambda_{2,t+1} \mu_{t+1}^{-\sigma} \frac{z_t^i}{z_{t+1}^i} s a_{t+1}^i \left(\frac{i_{t+1}}{i_t} \mu_{t+1}^i\right)^2 \left(\frac{i_{t+1}}{i_t} \mu_{t+1}^i - \mu_I\right) \tag{C.10}$$

$$k_{t+1} = \left(1 - \delta\left(u_t\right)\right) \frac{k_t}{\mu_t^i} + a_t^i i_t \left[1 - \frac{s}{2}\left(\frac{i_t}{i_{t-1}} \mu_t^i - \mu_I\right)^2\right] \tag{C.11}$$

$$r_t^k = \left(\mu_t^i\right)^{1-\alpha_k} a_t^n u_t^{\alpha_k - 1} \alpha_k k_t^{\alpha_k - 1} h_t^{\alpha_h} L^{1-\alpha_k-\alpha_h} \tag{C.12}$$

$$w_t = \left(\mu_t^i\right)^{-\alpha_k} a_t^n u_t^{\alpha_k} \alpha_h k_t^{\alpha_k} h_t^{\alpha_h - 1} L^{1-\alpha_k-\alpha_h} \tag{C.13}$$

$$w_t^h = \frac{w_t}{\eta_{w,t}} \tag{C.14}$$

$$y_t = c_t + \mu_t^g g_t + i_t \text{ where } \mu_t^g = \left(\mu_{t-1}^g\right)^{\rho_{xg}} \left(\mu_t\right)^{-1} \tag{C.15}$$

$$y_t = a_t^n \left(\mu_t^i\right)^{-\alpha_k} u_t^{\alpha_k} k_t^{\alpha_k} h_t^{\alpha_h} L^{1-\alpha_k-\alpha_h} \tag{C.16}$$

C.3 Model with Nominal Rigidities Equilibrium Conditions

$$n_t = \left(c_t - \kappa \frac{c_{t-1}}{\mu_t}\right)^{\gamma} \frac{n_{t-1}^{1-\gamma}}{\mu_t^{1-\gamma}} \tag{C.17}$$

$$v_t = c_t - \kappa \frac{c_{t-1}}{\mu_t} - \psi h_t^{\nu} n_t \tag{C.18}$$

$$b_t v_t^{-\sigma} - \beta\kappa E_t b_{t+1} \frac{1}{\mu_{t+1}^{\sigma}} v_{t+1}^{-\sigma} - \lambda_{3t}\gamma \frac{n_t}{c_t - \kappa \frac{c_{t-1}}{\mu_t}} + \beta\kappa\gamma E_t \frac{1}{\mu_{t+1}^{\sigma}} \lambda_{3t+1} \frac{n_{t+1}}{c_{t+1} - \frac{\kappa c_t}{\mu_{t+1}}} = \lambda_{1t} \tag{C.19}$$

$$-b_t v_t^{-\sigma} \psi \nu h_t^{\nu-1} n_t + \lambda_{1t} w_t^h = 0 \tag{C.20}$$

$$-\psi b_t v_t^{-\sigma} h_t^{\nu} + \lambda_{3t} - (1-\gamma)\beta E_t \frac{1}{\mu_{t+1}^{\sigma}} \lambda_{3t+1} \frac{\mu_{t+1} n_{t+1}}{n_t} = 0 \tag{C.21}$$

$$\lambda_{1,t} \frac{1}{R_t} \pi_{t+1} = \beta \lambda_{1,t+1} \mu_{t+1}^{-\sigma} \tag{C.22}$$

$$\lambda_{2,t} = \beta E_t \left[\lambda_{1,t+1} \mu_{t+1}^{-\sigma} \frac{z_t^i}{z_{t+1}^i} \left(r_{t+1}^k u_{t+1} - \widetilde{a}\left(u_{t+1}\right)\right) + \lambda_{2,t+1} \mu_{t+1}^{-\sigma} \frac{z_t^i}{z_{t+1}^i} (1-\delta)\right] \tag{C.23}$$

$$r_t^k = \left[a_1 + a_2\left(u_t - 1\right)\right] \tag{C.24}$$

$$\lambda_{1,t} = \lambda_{2,t} \left[a_t^i \left(1 - \frac{s}{2}\left(\mu_t^i \frac{i_t}{i_{t-1}} - \mu_I\right)^2\right) - s a_t^i \frac{i_t}{i_{t-1}} \mu_t^i \left(\frac{i_t}{i_{t-1}} \mu_t^i - \mu_I\right)\right] \tag{C.25}$$

$$+\beta E_t \lambda_{2,t+1} \mu_{t+1}^{-\sigma} \frac{z_t^i}{z_{t+1}^i} s a_{t+1}^i \left(\frac{i_{t+1}}{i_t} \mu_{t+1}^i\right)^2 \left(\frac{i_{t+1}}{i_t} \mu_{t+1}^i - \mu_I\right) \tag{C.26}$$

$$y \frac{1}{\eta_p - 1} \left(\widetilde{p}_t - MC_t \eta_{p,t}\right) + \theta_p E_t \ \frac{1}{R_{ss}} \ B_{ss}^p \mu \left(\frac{\widetilde{p}_t}{\widetilde{p}_{t+1}} \ \left(\pi_t\right)^{\tau_p} \left(\pi_{ss}\right)^{1-\tau_p} - \pi_{t+1}\right) = 0 \tag{C.27}$$

$$k_{t+1} = (1-\delta) \frac{k_t}{\mu_t^i} + a_t^i i_t \left[1 - \frac{s}{2}\left(\frac{i_t}{i_{t-1}} \mu_t^i - \mu_I\right)^2\right] \tag{C.28}$$

$$r_t^k = MC_t \left(\mu_t^i\right)^{1-\alpha_k} \left(a_t^n\right)^{\alpha_h} u_t^{\alpha_k - 1} \alpha_k k_t^{\alpha_k - 1} h_t^{\alpha_h} \tag{C.29}$$

$$w_t = MC_t \left(\mu_t^i\right)^{-\alpha_k} \left(a_t^n\right)^{\alpha_h} u_t^{\alpha_k} \alpha_h k_t^{\alpha_k} h_t^{\alpha_h - 1} \tag{C.30}$$

$$(1-\theta_p)\, \widetilde{p}_t^{\,-\frac{1}{\eta_p - 1}} + \theta_p \left[\left(\frac{\pi_{t-1}}{\pi_t}\right)^{\tau_p} \left(\frac{\pi_{ss}}{\pi_t}\right)^{1-\tau_p}\right]^{-\frac{1}{\eta_p - 1}} = 1 \tag{C.31}$$

$$h_{ss} \frac{1}{\eta_w - 1} \ \left(\widetilde{w}_t - w_t^h \eta_{w,t}\right) + \theta_w E_t \frac{1}{R_{ss}} B_{ss}^w \mu \left(\frac{\widetilde{w}_t}{\widetilde{w}_{t+1}} \frac{1}{\mu_{t+1}} \ \left(\pi_t \mu_t\right)^{\tau_w} \left(\pi_{ss}\mu_{ss}\right)^{1-\tau_w} - \pi_{t+1}\right) \ = 0 \tag{C.32}$$

$$(1-\theta_w) \left(\frac{\widetilde{w}_t}{w_t}\right)^{-\frac{1}{\eta_w - 1}} + \theta_w \left[\frac{w_{t-1}}{w_t} \frac{1}{\mu_t} \frac{1}{\pi_t} \left(\pi_{t-1}\mu_{t-1}\right)^{\tau_w} \left(\pi_{ss}\mu_{ss}\right)^{1-\tau_w}\right]^{-\frac{1}{\eta_w - 1}} = 1 \tag{C.33}$$

$$y_t = c_t + g_t + i_t + a(u_t)\mu_t^i k_t \tag{C.34}$$

$$y_t = (a_t^n)^{\alpha_h}\,\mu_{zn,t}^{-\alpha_k}\left(\frac{z_{t-1}^i}{z_t^i}\right)^{\frac{\alpha_k}{1-\alpha_k}} u_t^{\alpha_k} k_t^{\alpha_k} h_t^{\alpha_h} \; - fc = (a_t^n)^{\alpha_h}\left(\mu_t^i\right)^{-\alpha_k} u_t^{\alpha_k} k_t^{\alpha_k} h_t^{\alpha_h} \; - fc \tag{C.35}$$

$$\ln R_t = \ln R_{ss} + \rho_R \ln R_{t-1} + (1-\rho_R)\left[s_\pi \ln\left(\frac{\pi_t}{\pi^*}\right) + s_y \ln\left(\frac{y_t}{y^*}\right) + s_{gy}\ln\left(\frac{g_{y,t}}{g_y^*}\right)\right] + \ln e_{R,t} \tag{C.36}$$

$$\ln \mu_{t+1} = \rho_\mu \ln \mu_t + (1-\rho_\mu)\ln \mu_{ss} + \varepsilon_{\mu,t+1} \tag{C.37}$$

$$\ln gvt_{t+1} = \rho_g \ln gvt_t + (1-\rho_g)\ln gvt_{ss} + \varepsilon_{g,t+1} \tag{C.38}$$

$$\ln e_{R,t+1} = \rho_{eR} \ln e_{R,t} + \varepsilon_{eR,t+1} \tag{C.39}$$

C.4 Extra Figures and Tables

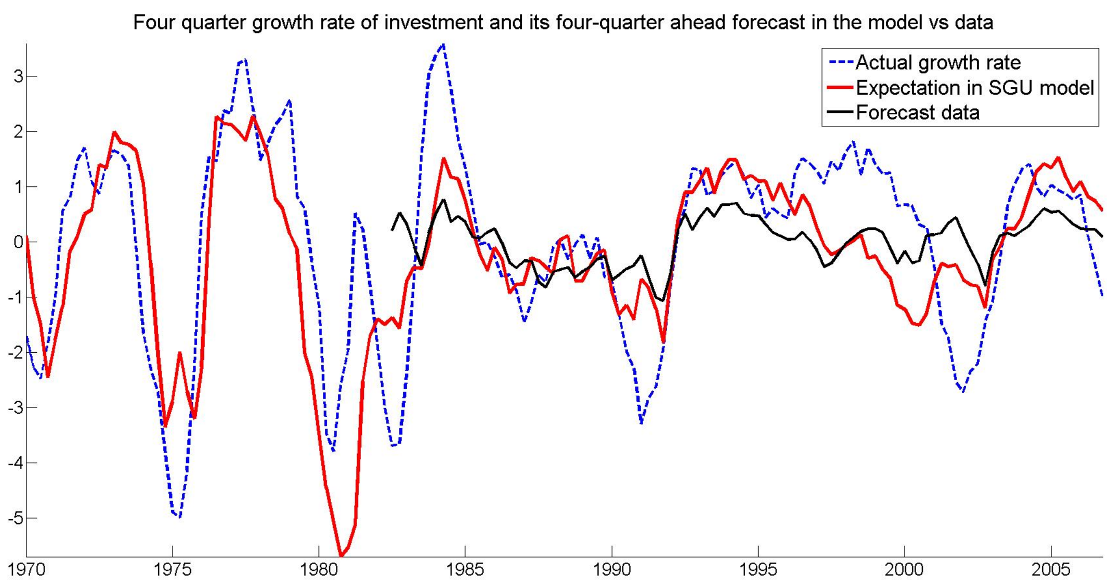

Figure A.1: SPF four-quarter investment growth rate forecast a year in advance and model-implied investment growth rate when estimated with data on expectations of output.

	$\Delta \ln y_{t,t-1}$	$\Delta \ln c_{t,t-1}$	$\Delta \ln I_{t,t-1}$	$\Delta \ln h_{t,t-1}$	$\Delta \ln G_{t,t-1}$	$\Delta \ln p_{inv,t-1,t}$	$\Delta \ln TFP_{t,t-1}$	$F_t \Delta \ln y_{t+2,t+1}$	$F_t \Delta lny_{t+4,t+3}$
Standard deviation									
Data	0.91	0.51	2.28	0.84	1.15	0.41	0.75	0.35	0.22
W/o forecast	0.65	0.75	2.67	0.83	1.13	0.40	0.79	0.42	0.38
W/ forecast	0.63	0.58	2.75	0.88	1.15	0.40	0.83	0.37	0.32
Correlation with gy									
Data	1.00	0.50	0.69	0.72	0.25	0.12	0.40	0.30	-0.02
W/o forecast	1.00	0.63	0.76	0.45	0.36	-0.02	0.30	0.46	0.24
W/ forecast	1.00	0.55	0.72	0.43	0.38	-0.01	0.24	0.45	0.20
Autocorrelation									
Data	0.28	0.20	0.52	0.59	0.05	0.49	-0.01	0.81	0.68
W/o forecast	0.49	0.37	0.59	0.13	0.02	0.48	0.03	0.60	0.52
W/ forecast	0.49	0.43	0.56	0.06	0.03	0.47	-0.02	0.81	0.78

Table A.1: Second moments

Note: Moments for quarterly forecast is for the period between 1970Q1 and 2006Q1 and the model-implied are ones estimated with data of the same period. The table reports the empirical moments (Data), in model estimated without forecast (W/o forecast rows) and in model estimated with forecast (W/ forecast row). The model moments are reported at posterior mean of the distribution computed from the last 200,000 draws.

Table A.2: Complete variance decomposition for all variables estimated in the baseline model with forecast between 1955Q1 and 2006Q4

Innovation	$\Delta \ln y_{t,t-1}$	$\Delta \ln c_{t,t-1}$	$\Delta \ln I_{t,t-1}$	$\Delta \ln h_{t,t-1}$	$\Delta \ln G_{t,t-1}$	$\Delta \ln p_{inv,t-1,t}$	$\Delta \ln TFP_{t,t-1}$	$\Delta \ln W_{t,t-1}$	$F_t \Delta \ln y_{t+2,t+1}$	$F_t \Delta lny_{t+4,t+3}$
Nonstationary TFP										
pd 0	13.35	5.50	7.88	1.23	3.95	0.00	12.40	8.57	21.43	18.82
pd 4	1.48	0.79	0.66	0.44	0.66	0.00	1.99	1.24	3.36	3.91
pd 8	3.04	1.65	1.34	1.10	1.63	0.00	5.07	3.00	7.35	9.13
Nonstationary IST										
pd 0	0.51	0.09	0.48	0.26	0.21	49.84	0.00	0.17	1.11	1.17
pd 4	0.12	0.02	0.14	0.04	0.05	11.43	0.00	0.05	0.21	0.17
pd 8	0.41	0.07	0.51	0.14	0.17	38.73	0.00	0.12	0.73	0.71
Government spending										
pd 0	8.81	0.36	1.10	1.59	88.10	0.00	0.00	0.88	2.22	1.99
pd 4	0.37	0.01	0.02	0.07	3.21	0.00	0.00	0.03	0.38	0.16
pd 8	0.23	0.01	0.01	0.05	2.02	0.00	0.00	0.02	0.25	0.12
Preference										
pd 0	16.87	78.65	5.14	4.16	0.00	0.00	0.00	1.17	5.86	6.47
pd 4	0.76	2.83	0.11	0.19	0.00	0.00	0.00	0.05	1.07	0.56
pd 8	0.43	1.60	0.05	0.11	0.00	0.00	0.00	0.03	0.62	0.37
Wage markup										
pd 0	6.93	2.89	6.48	26.85	0.00	0.00	0.00	18.30	7.85	6.63
pd 4	0.27	0.14	0.27	1.19	0.00	0.00	0.00	0.90	0.60	0.67
pd 8	7.43	4.34	7.15	37.59	0.00	0.00	0.00	29.12	18.04	22.02
Stationary TFP										
pd 0	3.47	0.13	5.91	16.49	0.00	0.00	68.31	26.48	2.19	1.65
pd 4	0.30	0.03	0.42	1.41	0.00	0.00	4.95	2.00	0.62	0.59
pd 8	0.43	0.05	0.58	2.06	0.00	0.00	7.28	2.92	1.01	1.17
Stationary IST										
pd 0	25.74	0.51	44.74	3.30	0.00	0.00	0.00	3.85	5.89	5.86
pd 4	5.01	0.15	9.39	0.93	0.00	0.00	0.00	0.62	10.15	8.53
pd 8	4.05	0.19	7.62	0.83	0.00	0.00	0.00	0.46	9.05	9.30

Table A.3: Complete variance decomposition for all variables estimated in the model with labor adjustment cost with forecast between 1955Q1 and 2006Q4

Innovation	$\Delta \ln y_{t,t-1}$	$\Delta \ln c_{t,t-1}$	$\Delta \ln I_{t,t-1}$	$\Delta \ln h_{t,t-1}$	$\Delta \ln G_{t,t-1}$	$\Delta \ln p_{inv,t-1,t}$	$\Delta \ln TFP_{t,t-1}$	$\Delta \ln W_{t,t-1}$	$F_t \Delta \ln y_{t+2,t+1}$	$F_t \Delta lny_{t+4,t+3}$
Nonstationary TFP										
pd 0	15.64	7.06	10.08	1.69	4.75	0.00	15.09	13.52	24.38	22.25
pd 4	1.16	0.66	0.59	0.18	0.51	0.00	1.55	0.98	2.54	2.99
pd 8	2.57	1.54	1.23	0.49	1.34	0.00	4.15	2.50	5.92	7.37
Nonstationary IST										
pd 0	0.51	0.13	0.47	0.19	0.21	52.66	0.00	0.16	1.09	1.18
pd 4	0.16	0.03	0.17	0.03	0.06	14.73	0.00	0.08	0.26	0.23
pd 8	0.34	0.07	0.40	0.10	0.14	32.61	0.00	0.14	0.61	0.61
Government spending										
pd 0	8.11	0.25	0.94	1.08	88.03	0.00	0.00	2.50	1.66	1.54
pd 4	0.32	0.01	0.02	0.02	3.08	0.00	0.00	0.14	0.32	0.14
pd 8	0.20	0.01	0.01	0.01	1.89	0.00	0.00	0.08	0.20	0.10
Preference										
pd 0	15.80	81.24	3.80	4.37	0.00	0.00	0.00	2.06	4.20	4.72
pd 4	0.38	1.62	0.05	0.05	0.00	0.00	0.00	0.11	0.50	0.27
pd 8	0.28	1.20	0.03	0.04	0.00	0.00	0.00	0.08	0.38	0.23
Wage markup										
pd 0	9.67	2.40	11.06	51.42	0.00	0.00	0.00	32.14	10.32	8.18
pd 4	0.16	0.05	0.20	0.57	0.00	0.00	0.00	0.31	0.33	0.35
pd 8	6.92	2.41	8.32	26.33	0.00	0.00	0.00	15.30	15.90	19.10
Stationary TFP										
pd 0	3.40	0.19	5.35	4.82	0.00	0.00	39.30	13.08	2.27	1.81
pd 4	0.66	0.06	0.94	0.68	0.00	0.00	8.09	1.83	1.32	1.34
pd 8	2.67	0.35	3.60	2.83	0.00	0.00	31.81	7.52	6.01	7.12
Stationary IST										
pd 0	22.13	0.45	37.36	2.84	0.00	0.00	0.00	6.11	4.15	4.27
pd 4	5.35	0.15	9.28	1.27	0.00	0.00	0.00	0.85	10.12	8.44
pd 8	3.56	0.13	6.10	0.99	0.00	0.00	0.00	0.53	7.51	7.78

Table A.4: Variance decomposition for sticky price model

Innovation	$\Delta \ln y_{t,t-1}$	$\Delta \ln c_{t,t-1}$	$\Delta \ln I_{t,t-1}$	$\Delta \ln h_{t,t-1}$	$\Delta \ln G_{t,t-1}$	$\Delta \ln p_{inv,t-1,t}$	$\Delta \ln TFP_{t,t-1}$	π	R	$\Delta \ln W_{t,t-1}$
Nonstationary TFP										
pd 0	18.99	21.54	10.91	3.38	3.82	0.00	29.09	6.40	13.92	17.56
pd 4	0.54	0.67	0.29	0.37	0.12	0.00	0.95	0.81	1.01	0.46
pd 8	0.08	0.12	0.04	0.07	0.02	0.00	0.17	0.16	0.21	0.08
Nonstationary IST										
pd 0	1.03	0.57	0.85	0.98	0.21	49.22	0.00	0.58	1.30	0.53
pd 4	0.13	0.07	0.12	0.08	0.03	5.85	0.00	0.05	0.11	0.07
pd 8	0.92	0.46	0.85	0.64	0.20	44.93	0.00	0.39	0.92	0.45
Government spending										
pd 0	3.71	0.10	0.10	1.68	69.81	0.00	0.00	0.09	0.34	0.34
pd 4	0.88	0.03	0.02	0.66	15.91	0.00	0.00	0.09	0.13	0.07
pd 8	0.55	0.02	0.01	0.40	9.89	0.00	0.00	0.06	0.09	0.05
Preference										
pd 0	6.84	63.17	0.33	5.36	0.00	0.00	0.00	0.87	0.96	0.99
pd 4	0.13	1.09	0.00	0.12	0.00	0.00	0.00	0.02	0.03	0.02
pd 8	0.15	1.28	0.00	0.14	0.00	0.00	0.00	0.03	0.04	0.02
Wage markup										
pd 0	4.86	5.03	3.75	42.95	0.00	0.00	0.00	4.98	11.45	23.86
pd 4	0.07	0.07	0.06	0.30	0.00	0.00	0.00	0.26	0.30	0.28
pd 8	0.05	0.06	0.04	0.22	0.00	0.00	0.00	0.19	0.25	0.22
Stationary TFP										
pd 0	4.13	1.13	5.22	17.59	0.00	0.00	69.25	16.29	27.42	11.86
pd 4	0.03	0.01	0.03	0.30	0.00	0.00	0.39	0.30	0.28	0.04
pd 8	0.01	0.00	0.01	0.11	0.00	0.00	0.14	0.11	0.11	0.01
Stationary IST										
pd 0	30.60	2.21	41.70	8.50	0.00	0.00	0.00	0.60	2.20	5.52
pd 4	7.07	0.45	9.72	2.94	0.00	0.00	0.00	2.57	3.00	1.31
pd 8	17.43	1.39	24.00	7.44	0.00	0.00	0.00	7.91	14.93	3.21
Price markup shock										
	1.81	0.52	1.94	3.93	0.00	0.00	0.00	6.20	7.58	32.42
Monetary policy shock										
	0.00	0.01	0.00	1.76	0.00	0.00	0.00	16.48	2.74	0.59
Interest rate target shock										
	0.00	0.00	0.00	0.10	0.00	0.00	0.00	34.57	10.68	0.04

Table A.5: Variance decomposition for sticky price model (continued)

Innovation	$F_t\Delta \ln y_{t+2,t+1}$	$F_t\Delta lny_{t+4,t+3}$	$F_t\pi_{t+1,t+2}$	$F_t\pi_{t+3,t+4}$
Nonstationary TFP				
pd 0	30.98	32.82	11.83	11.48
pd 4	0.98	1.11	1.22	0.62
pd 8	0.16	0.19	0.28	0.24
Nonstationary IST				
pd 0	1.90	2.22	0.52	0.51
pd 4	0.20	0.17	0.06	0.07
pd 8	1.51	1.48	0.47	0.51
Government spending				
pd 0	0.41	0.43	0.15	0.15
pd 4	0.82	0.41	0.12	0.06
pd 8	0.52	0.28	0.10	0.08
Preference				
pd 0	1.14	1.23	0.76	0.71
pd 4	0.15	0.09	0.04	0.02
pd 8	0.18	0.11	0.05	0.04
Wage markup				
pd 0	7.10	7.06	6.15	5.20
pd 4	0.12	0.13	0.33	0.18
pd 8	0.09	0.11	0.34	0.28
Stationary TFP				
pd 0	5.36	5.04	6.85	6.10
pd 4	0.05	0.05	0.38	0.16
pd 8	0.02	0.02	0.17	0.12
Stationary IST				
pd 0	3.42	3.07	1.06	1.11
pd 4	10.82	8.64	1.63	1.50
pd 8	31.66	32.96	8.83	7.80
Price markup shock				
	2.44	2.38	1.18	1.17
Monetary policy shock				
	0.00	0.00	1.62	0.56
Interest rate target shock				
	0.00	0.00	55.88	61.34