Trade and Uncertainty*

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Abstract

We attempt to explain why international trade is so volatile in response to economic shocks. We combine the uncertainty shock approach by Bloom (2009, Econometrica) with a model of international trade, extending the model to the open economy. Firms import intermediate inputs from foreign suppliers. Due to fixed costs of ordering firms hold an inventory of intermediates. We show that in response to an uncertainty shock firms optimally adjust their inventory policy by cutting their orders of foreign intermediates disproportionately strongly. In the aggregate, this response leads to a bigger contraction in international trade flows than in domestic economic activity. We confront the model with newly-compiled monthly aggregate U.S. import data, and industrial production data going back to 1962, and also with disaggregated data back to 1989. Our results suggest a tight link between uncertainty and the cyclical behavior of international trade.

Keywords: Uncertainty shock, trade collapse, inventory, real options, imports, intermediates

JEL Codes: E3, F1

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1 Introduction

The recent global economic crisis has been characterized by a sharp decline in economic output. However, the accompanying decline in international trade was even sharper, in some cases up to 50 percent. Standard models of international macroeconomics and international trade fail to account for the severity of the trade collapse.

In this paper, we attempt to explain why international trade is so volatile in response to economic shocks. On the theoretical side, we combine the uncertainty shock approach by Bloom (2009) with a model of international trade. Bloom's (2009) real-options approach is motivated by high-profile events that trigger an increase in uncertainty about the future path of the economy, for example the 9/11 terrorist attacks or the collapse of Lehman Brothers. In the wake of such events, firms adopt a 'wait-and-see' approach, slowing down their hiring and investment activities. Bloom (2009) shows that bouts of large uncertainty can be modeled as *second moment* shocks to demand or productivity and typically lead to sharp recessions. Once the degree of uncertainty subsides, firms revert to their normal hiring and investment patterns and the economy recovers.

We extend the uncertainty shock approach to the open economy. In contrast to Bloom's (2009) closed-economy set-up, we develop a theoretical framework in which firms import intermediate inputs from foreign suppliers. This production structure is motivated by the empirical observation that a large fraction of international trade consists of capital-intensive intermediate goods such as car parts and wind turbines.

Due to a fixed cost of ordering associated with transportation, firms hold an inventory of foreign intermediate inputs. Following the inventory model with variable uncertainty by Hassler (1996), we show that in response to a large uncertainty shock to the demand for final products, firms optimally adjust their inventory policy by cutting their orders of foreign intermediates more strongly than orders for domestic intermediates. In the aggregate, this differential response leads to a bigger contraction and subsequently a stronger recovery in international trade flows than in domestic economic activity. Thus, international trade exhibits a larger variance and is more volatile than domestic economic activity. In a nutshell, uncertainty shocks magnify the response of international trade.

Our model generates a set of additional predictions. First, the magnification effect is increased by larger fixed costs of ordering. Intuitively, the larger the fixed costs of ordering, the more reluctant firms are to order intermediate inputs from abroad if uncertainty rises. This is a testable hypothesis to the extent that fixed ordering costs vary across domestic and foreign trading partners.

Second, the magnification effect is muted for industries characterized by high depreci-

ation rates. Perishable goods are a case in point for extremely high depreciation rates. The fact that such goods have to be ordered frequently means that importers have little choice but to keep ordering them frequently even if uncertainty rises. Conversely, durable goods can be considered as the opposite case of very low depreciation rates. Our model predicts that for those goods we should expect the largest degree of magnification in response to uncertainty shocks. Intuitively, the option value of waiting can be most easily realized by delaying orders for durable goods. We find strong evidence of this pattern in the data when we examine the cross-industry response of imports to elevated uncertainty.

In sum, our model leads to various predictions in a unified framework. In contrast to conventional static trade models such as the gravity equation, we focus on the dynamic response of international trade. In addition, we focus on second moment shocks and thus move beyond the first moment shocks traditionally employed in the literature. Our approach is relevant for researchers and policymakers alike who seek to understand the recovery process in response to the Great Recession. It also helps to predict the trajectory of international trade for future economic crises.

On the empirical side, we confront the model with high-frequency monthly U.S. import and industrial production data going back to 1962. Our results suggest a tight link between uncertainty shocks as identified by Bloom (2009) and the cyclical behavior of international trade. That is, the behavior of trade can be well explained with standard uncertainty measures such as a VXO stock market volatility index. Bloom (2009) identifies 17 high-volatility episodes since the early 1960s such as the assassination of JFK, the 1970s oil price shocks, the Black Monday of October 1987, the 1998 bailout of Long-Term Capital Management, 9/11 and the collapse of Lehman Brothers in September 2008. As Bloom (2009) shows, these high-volatility episodes are strongly correlated with alternative indicators of uncertainty.

In particular, we argue that the Great Trade Collapse of 2008/09 can to a large extent be explained by the large degree of uncertainty triggered by the collapse of Lehman Brothers. According to our empirical results, the unusually large trade collapse of 2008/09 is thus a response to the unusually large increase in uncertainty at the time. Although it stands out quantitatively, qualitatively the Great Trade Collapse is comparable to previous post-World War II slowdowns or contractions in international trade. In fact, our aim is to empirically account for trade recessions more generally, not only for the Great Trade Collapse.

In addition, we exploit variation across sectors to test our theoretical predictions relating to the perishability and durability of goods as well as the degree of downstream intermediate use of imports. Overall, the data exhibit the patterns implied by the theory.

The trade collapse of 2008/09 has been documented by various authors (see Baldwin 2009 for a collection of approaches). Eaton, Kortum, Neiman and Romalis (2011) develop a structural model of international trade in which the decline in trade can be related to a collapse in demand for tradable goods and an increase in trade frictions. They find that a collapse in demand explains the vast majority of declining trade. Our approach is different in that we explicitly model the collapse in demand by considering second moment uncertainty shocks. Consumers and firms react to the uncertainty by adopting a 'wait-and-see' approach. Thus, we do not require an increase in trade frictions to account for the excess volatility of trade. This approach is consistent with the Global Trade Alert Report by Evenett (2010) who finds that protectionism was contained during the Great Recession.

Examining Belgian firm-level data during the 2008/09 recession, Behrens, Corcos and Mion (2012) find that most changes in international trade across trading partners and products occurred at the intensive margin, while trade fell most for consumer durables and capital goods. Levchenko, Lewis and Tesar (2010) stress that sectors used as intermediate inputs experienced substantially bigger drops in international trade. Likewise, Bems, Johnson and Yi (2011) confirm the important role of trade in intermediate goods. These findings are consistent with our modeling approach.

Our model is cast in terms of real variables, and we do not model monetary effects and prices. This modeling strategy is supported by the empirical regularity documented by Gopinath, Itskhoki and Neiman (2012) showing that prices of differentiated manufactured goods (both durables and non-durables) hardly changed during the trade collapse of 2008/09. They conclude that the collapse in the value of international trade in differentiated goods was "almost entirely a quantity phenomenon." We therefore focus on modeling real variables.[1]

Amiti and Weinstein (2011) and Chor and Manova (2012) highlight the role of financial frictions and the drying up of trade credit. However, based on evidence from Italian manufacturing firms Guiso and Parigi (1999) show that the negative effect of uncertainty on investment cannot be explained by liquidity constraints.

Engel and Wang (2011) point out the fact that the composition of international trade is tilted towards durable goods. Building a two-sector model in which only durable goods are traded, they can replicate the higher volatility of trade relative to general economic activity. Instead, we relate the excess volatility of trade to inventory adjustment in response to uncertainty shocks. As this mechanism in principle applies to any industry,

[1]However, prices of non-differentiated manufactures declined sharply. But in the empirical section we most heavily rely on differentiated products.

compositional effects do not drive the volatility of international trade in our model.

Finally, our paper is related to Alessandria, Kaboski and Midrigan (2010a and 2011) who rationalize the decline in international trade by changes in firms' inventory behavior driven by a first moment shock to the cost of labor and a shock to the interest rate. In contrast, we focus on the role of increased uncertainty, modeled as a second-moment shock. Heightened uncertainty was arguably a defining feature of the Great Recession, and we employ an observable measure of it.

The paper is organized as follows. In section 2 we show how impulse response functions for aggregate U.S. imports and U.S. industrial production react to uncertainty shocks. To further motivate our approach, we also highlight how conventional static trade models, especially in the form of the gravity equation, fail to explain the extent of the Great Trade Collapse of 2008/09. In section 3, 4 and 5 we outline our theoretical model, conduct comparative statics and provide theoretical simulation results. Section 6 presents the empirical evidence. In section 7 we ask to what extent uncertainty shocks can empirically account for the Great Trade Collapse. Section 8 concludes.

2 Motivation: Uncertainty Shocks and International Trade

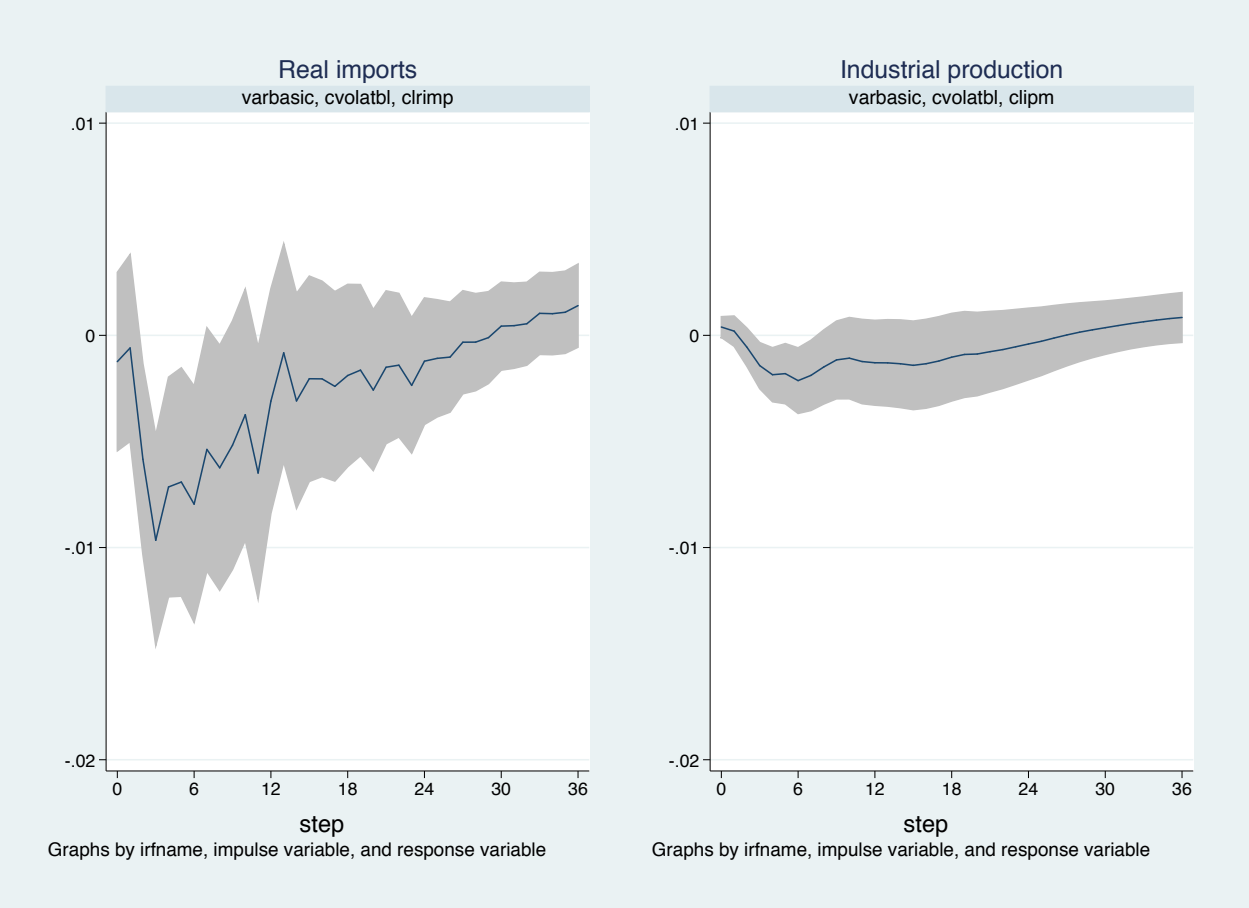
The world witnessed an unusually steep decline in international trade during the Great Recession of 2008/09, generally the steepest since the Great Depression. International trade plummeted by 30 percent or more in many cases. Some countries suffered particularly badly. For example, Japanese trade declined by about 50 percent from September 2008 to February 2009.

In addition, the decline was remarkably synchronized across countries. Baldwin (2009, introductory chapter) notes that "all 104 nations on which the WTO reports data experienced a drop in both imports and exports during the second half of 2008 and the first half of 2009." The synchronization hints at a common cause.

To motivate our approach, we first showcase the simplest possible evidence on the importance of uncertainty shocks for trade using aggregate data on real imports and industrial production (IP). We estimate a simple vector autoregression (VAR) with monthly data through February 2012, following Bloom (2009) exactly (see the empirical section for details).

Figure 1 presents the VAR results for both imports and IP side by side. The impulse response functions (IRFs) are based on a one-period uncertainty shock where the Bloom uncertainty indicator increases by one unit (again, we describe the details in the empirical section). The bottom line is very clear from this figure. In response to the uncertainty

Figure 1: IRFs at Aggregate Level for Uncertainty Shocks



Source: Sample is 1962:1–2012:2. Imports from various sources, deflated by CPI; all other data as in Bloom (2009), updated. Uncertainty shocks for quadvariate VARs as in Bloom (2009). Ordering is stock market, volatility, log employment, followed lastly by either log real imports or log IP. Data updated through February 2012. No rescaling of shocks. 95% confidence intervals shown. See text.

shock, both industrial production and imports decline. But the response of imports is considerably stronger, about 5 to 10 times as strong in its period of peak impact during year one. The response of imports is also highly statistically significant. At its peak the IRF is 3 or 4 standard errors below zero, whereas the IRF for IP is only just about 2 standard errors below zero, and only just surmounts the 95% confidence threshold.

2.1 The Great Trade Collapse and the Failure of Gravity

While we will argue throughout the paper that uncertainty shocks can go a long way in explaining the behavior of international trade in recessions in general and during the Great Trade Collapse in particular, standard gravity approaches fall short of this objective.

As a motivation, consider the workhorse gravity equation by Anderson and van Wincoop (2003):[2]

$$x_{ij} = \frac{y_i y_j}{y^W} \left(\frac{t_{ij}}{\Pi_i P_j} \right)^{1-\sigma},$$

where x_{ij} denotes imports to country i from country j, y_i and y_j denote the incomes of the two countries, y^W denotes world income, t_{ij} are bilateral trade costs, and Π_i and P_j are outward and inward multilateral resistance, respectively, which can be interpreted as average outward and inward bilateral trade costs. Taking logs and first differences yields

$$\Delta \ln \left(x_{ij} \right) = \Delta \ln \left(y_i \right) + \Delta \ln \left(y_j \right) - \Delta \ln \left(y^W \right) - (\sigma + 1) \Delta \ln \left(t_{ij} \right) + (\sigma + 1) \Delta \ln \left(\Pi_i P_j \right).$$

As most evidence indicates that trade costs and policy barriers moved very little during the recession (Evenett 2010), let us assume for simplicity that bilateral and average trade costs were unchanged:[3]

$$\Delta \ln \left(t_{ij} \right) = \Delta \ln \left(\Pi_i P_j \right) \approx 0.$$

To carry out a simple back-of-the-envelope calculation we suppose that income dropped by about 6 percent on average for OECD countries and around 3 percent for the global economy. It follows that bilateral trade amongst OECD countries should have dropped by only 9 percent on average:

$$\begin{aligned} \Delta \ln \left(x_{ij} \right) &\approx \Delta \ln \left(y_i \right) + \Delta \ln \left(y_j \right) - \Delta \ln \left(y^W \right) \\ &= -6 \text{ percent} - 6 \text{ percent} + 3 \text{ percent} = -9 \text{ percent}. \end{aligned}$$

However, in the data we observe a drop of around 30 percent. Clearly, the traditional gravity framework fails to explain the Great Trade Collapse.

We note that in the absence rising trade costs, 'back-and-forth trade' or 'vertical specialization' generally cannot explain the excessive responsiveness of trade to the decline in income. For example, if demand for the final good drops by 10 percent, then demand for intermediates in all stages is also expected to drop by 10 percent. If trade cost elasticities are sufficiently high, only an increase in bilateral trade frictions such as a tariff hike or sudden protectionism could explain a disproportionately strong decline in trade. But there is little evidence of increased protectionism during the Great Recession (Evenett

[2]Similar gravity equations can be derived from the models by Eaton and Kortum (2002) and Chaney (2008).

[3]The assumption of constant multilateral resistance also entails that world income shares did not change, e.g. the U.S. share of world income was constant. We maintain this assumption here as a rough approximation.

2010), while freight rates declined for most modes of shipping.

3 A Model of Trade with Uncertainty Shocks

We build on Hassler's (1996) setting of investment under uncertain demand to construct a model of trade in intermediate goods. Following the seminal contribution by Bloom (2009) we then introduce second moment uncertainty shocks.

Hassler's (1996) model starts from the well-established premise that uncertainty has an adverse effect on investment. In our set-up we model 'investment' as firms' investing in intermediate goods. Due to fixed costs of ordering firms build up an inventory of intermediate goods that they run down over time and replenish at regular intervals. The intermediate goods can be either ordered domestically or imported from abroad. Thus, we turn the model into an open economy set-up.

In addition, firms face uncertainty over 'business conditions,' which means they experience unexpected fluctuations in productivity and demand. What's more, the degree of uncertainty varies over time. Firms might therefore enjoy periods of calm when business conditions are relatively stable, or they might have to weather 'uncertainty shocks' that lead to a volatile business environment characterized by large fluctuations. Overall, this formulation allows us to model the link between production, international trade and shifting degrees of uncertainty. Hassler's (1996) key innovation is to formally model how *changes* in uncertainty influence investment. His model therefore serves as a natural starting point for our analysis of uncertainty shocks.

3.1 Production and Demand

As in Bloom (2009), each firm has a Cobb-Douglas production function

$$F(A, K, L) = AK^{\alpha}L^{1-\alpha}, \tag{1}$$

where A is productivity, L is domestic labor and K is an intermediate input that depreciates at rate δ. Each firm faces isoelastic demand Q with elasticity ε

$$Q = BP^{-\varepsilon}, \tag{2}$$

where B is a demand shifter. As we focus on the firm's short-run behavior, we assume that the firm takes the wage rate and the price of the intermediate input as given.[4] We thus adopt a partial equilibrium approach to keep the model tractable.

3.2 Inventory and Trade

The input K is an intermediate good (or a composite of such goods). As firms have to pay fixed costs of ordering per shipment f, they store the intermediate as inventory and follow an s, S inventory policy. Scarf (1959) shows that in the presence of such fixed costs of ordering, an s, S policy is an optimal solution to the dynamic inventory problem. We assume that the intermediate good can be ordered either domestically or from abroad, leading to domestic trade flows or imports. The corresponding fixed costs are f_D and f_F with $f_D \leq f_F$, where D stands for domestic and F for foreign.

Given the intermediate input price and the wage rate, it follows that the firm employs a constant ratio of intermediates and labor regardless of productivity fluctuations. That is, the Cobb-Douglas production function (1) implies that the firm's use of intermediates K is proportional to output Q. Similar to Hassler (1996) we assume that the firm has a target level of intermediates to be held as inventory, denoted by K^*, which is proportional to output Q. Thus, we can write

$$k^* = c + q, \tag{3}$$

where c is a constant, $k^* \equiv \ln(K^*)$ denotes the logarithmic target and $q \equiv \ln(Q)$ denotes logarithmic output.

We follow Hassler (1996) in modeling the dynamic inventory problem. In particular, we assume a quadratic loss function that penalizes deviations z from the target k^* as $\frac{1}{2}z^2$ with $z \equiv k - k^*$. Clearly, in the absence of ordering costs ($f = 0$) the firm would continuously set k equal to the target k^*. However, with positive ordering costs ($f > 0$) the firm faces a non-trivial trade-off as it needs to balance the fixed costs on the one hand and the costs of deviating from the target on the other.

We solve for the optimal solution to this inventory problem subject to a stochastic process for output q. The optimal control solution can be characterized as follows: when deviation of inventory z reaches a lower trigger point s, the firm orders the amount ϕ so that the inventory rises to a return point of deviation $S = s + \phi$.Formally, we can state the

[4]We will mainly think of the intermediate input as imported from abroad. The prices of differentiated manufactured goods in international trade were essentially unchanged during the trade collapse of 2008/09, as documented by Gopinath, Itskhoki and Neiman (2012). Their evidence further motivates our assumption of a given input price.

problem as

$$\min_{\{I_t,z_t\}_0^\infty} \left\{ \mathrm{E}\,0 \int_0^\infty e^{-rt} \left(\frac{1}{2} z_t^2 + I_t f \right) \mathrm{d}\,t \right\} \tag{4}$$

subject to

$$\begin{aligned} z_0 &= \bar{z}, \\ z_{t+\mathrm{d}\,t} &= \begin{cases} \text{free} & \text{if } k_t \text{ is adjusted,} \\ z_t - \delta\,\mathrm{d}\,t - \mathrm{d}\,q & \text{otherwise,} \end{cases} \\ I_t\,\mathrm{d}\,t &= \begin{cases} 1 & \text{if } k_t \text{ is adjusted,} \\ 0 & \text{otherwise,} \end{cases} \end{aligned}$$

I_t is a dummy variable that takes on the value 1 whenever k_t is adjusted, r is a constant discount factor, and δ is the depreciation rate for the intermediate so that $\mathrm{d}\,K_t/K = \delta\,\mathrm{d}\,t$.[5]

3.3 Business Conditions with Time-Varying Uncertainty

Due to market clearing output can move because of shifts in productivity A in equation (1) or demand shifts B in equation (2). Like Bloom (2009), we refer to the combination of supply and demand shifts as *business conditions*. Specifically, we assume that output q follows a stochastic marked point process that is known to the firm. With an instantaneous probability $\lambda/2$ per unit of time, q shifts up or down by the amount ε:

$$q_{t+\mathrm{d}\,t} = \begin{cases} q_t + \varepsilon & \text{with probability } (\lambda/2)\,\mathrm{d}\,t, \\ q_t & \text{with probability } 1 - \lambda\,\mathrm{d}\,t, \\ q_t - \varepsilon & \text{with probability } (\lambda/2)\,\mathrm{d}\,t. \end{cases} \tag{5}$$

The shock ε can be interpreted as a sudden change in business conditions. Through the proportionality between output and the target level of inventory embedded in equation (3) a shift in q leads to an updated target inventory level k^*. Following Hassler (1996) we assume that ε is sufficiently large such that it becomes optimal for the firm to adjust k.[6] That is, a positive shock to output increases k^* sufficiently to lead to a negative deviation z that reaches below the lower trigger point s. As a result the firm restocks k. Vice versa, a negative shock reduces k^* sufficiently such that z reaches above the upper trigger point

[5]The intermediate factor K is a stock variable in our model. In our trade and production data at the 4-digit industry level, examples of such factors include 'electrical equipment', 'engines, turbines, and power transmission equipment', 'communications equipment' and 'railroad rolling stock.' We can think of the firm described in our model as ordering a mix of such products.

[6]Hassler (1996, section 4) reports that relaxing the large shock assumption, while rendering the model more difficult to solve, appears to yield no qualitatively different results.

and the firm destocks k. Thus, to keep our model tractable we allow firms to both restock and destock depending on the direction of the shock.

The arrival rate of shocks λ is the measure of uncertainty and thus a key parameter of interest. We interpret changes in λ as changes in the degree of uncertainty. Note that λ determines the frequency of shocks, not the size of shocks. This feature is consistent with λ determining the *second moment* of shocks, not their *first moment*. More specifically, as the simplest possible set-up we follow Hassler (1996) by allowing uncertainty λ_ω to switch stochastically between two states $\omega \in \{0, 1\}$: a state of low uncertainty λ_0 and a state of high uncertainty λ_1 with $\lambda_0 < \lambda_1$. The transition of the uncertainty states follows a Markov process

$$\omega_{t+\mathrm{d}\,t} = \begin{cases} \omega_t & \text{with probability } 1 - \gamma_\omega \,\mathrm{d}\,t, \\ \overline{\omega}_t & \text{with probability } \gamma_\omega \,\mathrm{d}\,t, \end{cases} \tag{6}$$

where $\overline{\omega}_t = 1$ if $\omega_t = 0$, and vice versa. The probability of switching the uncertainty state in the next instant $\mathrm{d}\,t$ is therefore $\gamma_\omega \,\mathrm{d}\,t$, with the expected duration until the next switch given by γ_ω^{-1}. Below we will choose parameter values for λ_0, λ_1, γ_0 and γ_1 that are consistent with uncertainty fluctuations as observed over the past few decades.[7]

3.4 Solving the Inventory Problem

The Bellman equation for the inventory problem is

$$\begin{aligned} V(z_t, \omega_t) &= \frac{1}{2} z_t^2 \,\mathrm{d}\,t + (1 - r \,\mathrm{d}\,t)\, \mathrm{E}_t V(z_{t+\mathrm{d}\,t}, \omega_{t+\mathrm{d}\,t}) \\ &= \frac{1}{2} z_t^2 \,\mathrm{d}\,t + (1 - r \,\mathrm{d}\,t)\left(V(z_t) - \delta \,\mathrm{d}\,t V_z(z_t) + \lambda \,\mathrm{d}\,t \left(V(S) + f - V(z)\right)\right). \end{aligned} \tag{7}$$

We set $\mathrm{d}\,t^2 = 0$, divide by $\mathrm{d}\,t$ and collect terms to obtain the following differential equation:

$$(r + \lambda) V(z) + \delta V_z(z) = \frac{1}{2} z^2 + \lambda \left(V(S) + f\right). \tag{8}$$

This is a standard differential equation. [Technical appendix: Fill in solution here including the value-matching condition and the smooth-pasting condition. Extend to the case of time-varying uncertainty.]

We evaluate equation (8) at the lower trigger point s and at the return point S. Then

[7] Overall, the stochastic process for uncertainty is consistent to Bloom's (2009). In his setting uncertainty also switches between two states (low and high uncertainty) with given transition probabilities.

we subtract the second equation from the first to obtain

$$(r+\lambda)\left(V\left(s\right)-V(S)\right)+\delta\left(V_z(s)-V_z(S)\right)=\frac{1}{2}\left(s^2-S^2\right).$$

The first term on the left-hand side is equal to $(r+\lambda)f$ by the value-matching condition, and the second term is zero by the smooth-pasting condition. It follows

$$\frac{1}{2}\left(s^2-S^2\right)=rf+\lambda f>0.$$

Note that since lower trigger point is expressed as a deviation, we have $s<0$. The return point S is always positive. It follows $-s>S$. This means that the inventory level is on average below the target. This reflects the uncertainty and the option value of waiting. Intuitively, in the absence of uncertainty the firm would stock as much inventory as to be at the target value on average. That is, its inventory would be above and below the target exactly half of the time. However, in the presence of uncertainty it becomes optimal for the firm to adopt a more cautious stance. Given that output q and thus the target level k^* are stochastic according to equation (5), the firm is better off holding less inventory on average and placing a large order only once the need arises. This logic follows immediately from the literature on uncertainty and the option value of waiting (McDonald and Siegel 1986, Dixit 1989, Pindyck 1991).

4 Comparative Statics

The main purpose of this section is to explore how firms endogenously change the s, S bounds in response to increased uncertainty. Our key result is that firms lower the s, S bounds in response to increased uncertainty. In addition, we are interested in comparative statics for the depreciation rate δ and the fixed cost of ordering f. As explained by Hassler (1996), the model cannot be solved analytically. Numerical methods must be used but they uniquely define $V(z)$ in the Bellman equation (7).

4.1 Parameterizing the Model

We choose the same parameter values for the interest rate and rate of depreciation as in Bloom (2009), i.e., $r=0.065$ and $\delta=0.1$ per year. For the stochastic uncertainty process described by equations (5) and (6) we choose parameter values that are consistent with Bloom's (2009) data on stock market volatility. In his Table II he reports that an uncer-

tainty shock has an average half-life of two months. This information can be expressed in terms of the transition probabilities in equation (6) with the help of a process of exponential decay for a quantity D_t

$$D_t = D_0 \exp(-gt).$$

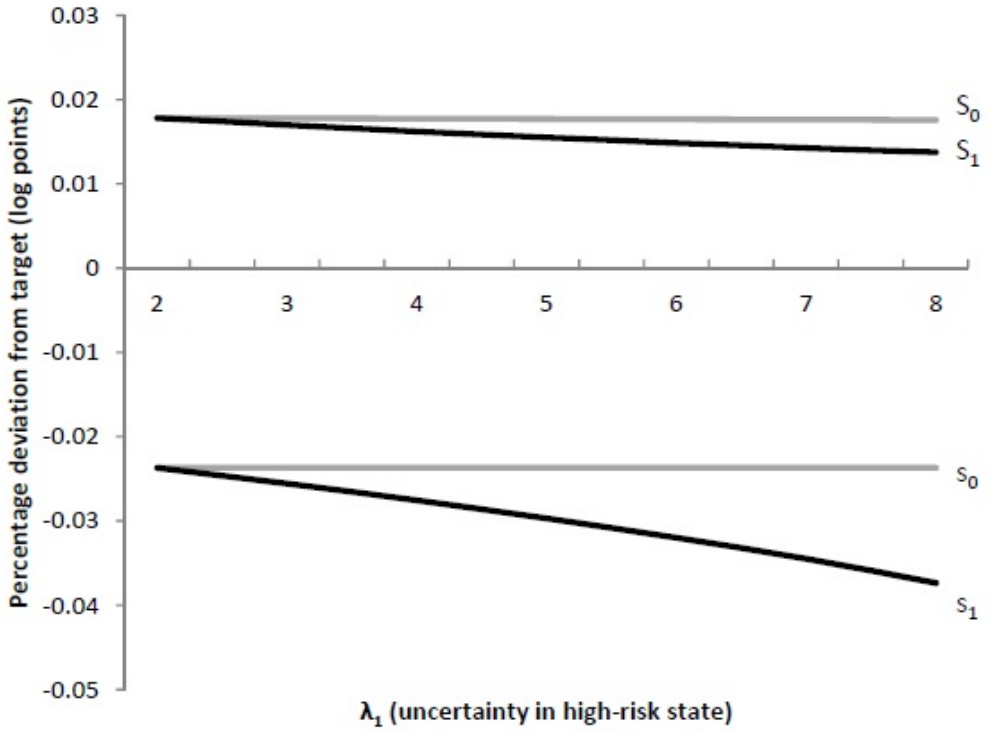
Setting t equal to 2 months yields a rate of decay $g = 0.3466$ for D_t to halve. The decaying quantity D_t in that process can be thought of as the number of discrete elements in a certain set. Then we can compute the average length of time that an element remains in the set, which corresponds to the expected duration of the high-uncertainty state, γ_1^{-1}. This is the mean lifetime of the decaying quantity, and it is given by $1/g$.Thus, the average duration of the high-uncertainty period corresponds to $1/0.3466$=2.8854 months or 0.2404 years in this case. It follows $\gamma_1 = 1/0.2404 = 4.1588$ when the duration is expressed in years.

Bloom (2009) furthermore reports 17 uncertainty shocks in 46 years. Hence, an uncertainty shock arrives on average every 46/17=2.71 years, or 32.5 months. Ignoring the relatively short duration of high-uncertainty periods, this means an average duration of the low-uncertainty period of 2.71 years. It follows $\gamma_0 = 1/2.7059 = 0.3696$.

The uncertainty term $\lambda \, \mathrm{d}\, t$ in the marked point process (5) indicates the probability that output is hit by a supply or demand shock in the next instant that is sufficiently large to shift the target level of inventory. Thus, the expected length of time until the next shock is $1/\lambda$. It is difficult to come up with an empirical counterpart of the frequency of such shocks since they are unobserved. For the baseline level of uncertainty we set $\lambda_0 = 2$, which implies that shocks hit on average every 1/2=0.5 years. However, we note that the results are not very sensitive to the λ_0 value. In our baseline specification we follow Bloom (2009, Table II) in setting the value for the high-uncertainty state twice as large as in the low-uncertainty state, i.e., $\lambda_1 = 2\lambda_0 = 4$. But in the comparative statics below we experiment with a range of values for λ_1.

Finally, we need to find an appropriate value for the fixed costs of ordering f. Based on data for a US steel manufacturer Alessandria et al. (2010b) report that "domestic goods are purchased every 85 days, while foreign goods are purchased every 150 days." To match the behavior of foreign import flows we set f to ensure that the interval between orders is on average 150 days in the low-uncertainty state. This implies $f_F = 0.0000588$ as our baseline value. Matching the interval of 85 days for domestic flows would imply $f_D = 0.00001066$. However, we show in the simulation section that quantitatively that we already obtain large declines in trade flows for fixed costs that are not as high as f_F in our baseline specification. That is, we obtain a large decline in trade flows for a lower ratio of f_F/f_D as implied by the above values. [Compare to Alessandria et al. (2010b).]

Figure 2: Change in s, S bounds due to higher uncertainty. The low-uncertainty state is in grey, the high-uncertainty state is in black.



4.2 A Rise in Uncertainty

Given the above parameter values we solve the model numerically. Figure 2 illustrates the change in s, S bounds in response to a rising level of uncertainty λ. Note that there are two sets of s, S bounds: one set for the low-uncertainty state 0, and the other for the high-uncertainty state 1. The level of low uncertainty is fixed at $\lambda_0 = 2$ but the level of high uncertainty λ_1 varies on the horizontal axis. As the s, S bounds are endogenous, all of them in principle shift in response to a change in one of the model's parameters. But clearly, the bounds for the low-uncertainty state are hardly affected by changes in λ_1.

The vertical scale indicates the percentage deviation from the target k^*. Two observations stand out. First, the bounds for the high-uncertainty state are lower, i.e., $S_1 < S_0$ and $s_1 < s_0$. Second, the negative deviations for the lower trigger points s_0 and s_1 are higher in absolute value than positive deviations for the return points S_0 and S_1, i.e., $|s_1| < S_1$ and $|s_0| < S_0$. On average the firm's inventory is thus below target. This reflects the option value of waiting.

Figure 3: How uncertainty decreases the lower trigger point.(compared to the low-uncertainty state).

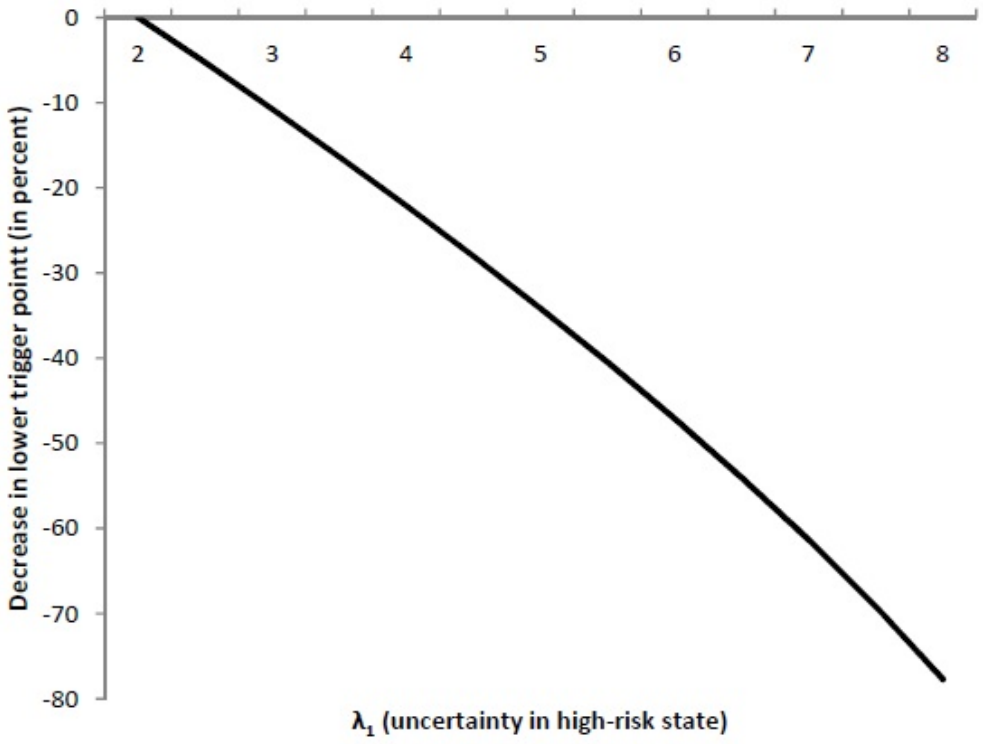
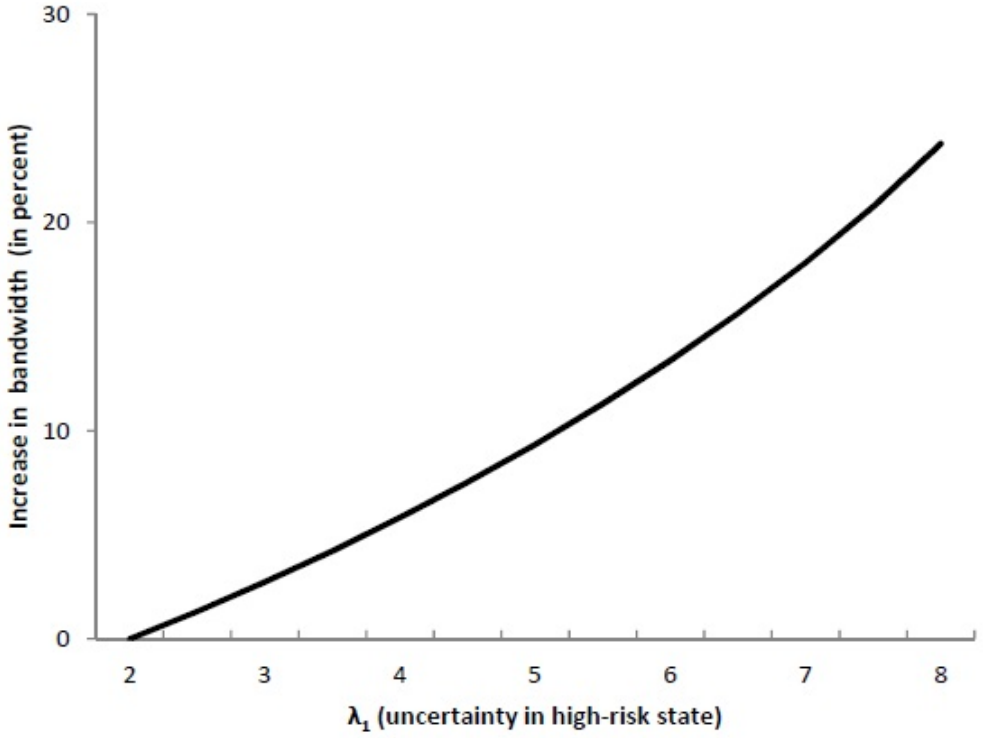


Figure 2 illustrates that the firm optimally responds to increased uncertainty by lowering both s, S bounds for the high-uncertainty state. Figure 3 shows that the decline in the lower trigger point s_1 compared to s_0 can be quite substantial for high degrees of uncertainty. Intuitively, when uncertainty rises, the firm becomes more cautious and adopts a wait-and-see attitude. It runs down its inventory further than in the low-uncertainty state, and it does not stock up to as high a level. It turns out that the firm lowers s_1 more than S_1 so that the bandwidth $(S_1 - s_1)$ rises in response to higher uncertainty. Figure 4 plots this increase in bandwidth.

4.3 Varying the Depreciation Rate

Some types of imports are inherently difficult to store as inventory, for instance food products and other perishable goods. We model this inherence difference in storability with a higher rate of depreciation. Figure 5 illustrates the effect of a higher depreciation rate that doubles to $\delta = 0.2$ compared to the baseline scenario of $\delta = 0.1$ in Figure 3. In general,

Figure 4: How uncertainty increases the s, S bandwidth (compared to the low-uncertainty state).

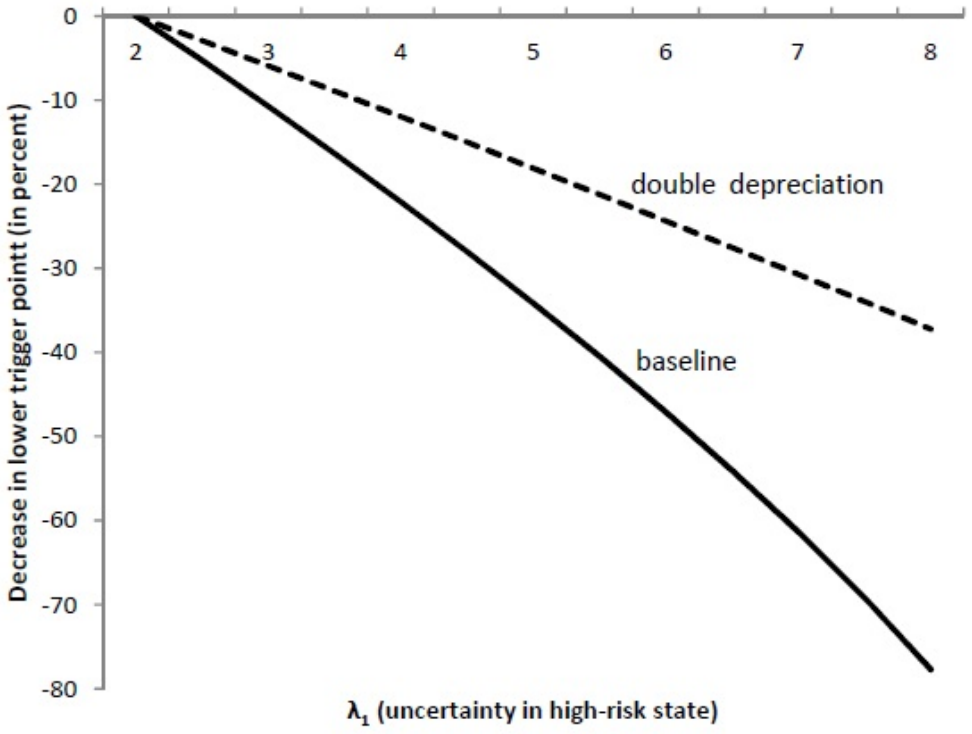


the larger the depreciation rate, the smaller the decreases in s_1 and S_1. Intuitively, with a larger depreciation rate the firm orders more frequently. The value of waiting is therefore not as important and does not respond as strongly to changes in uncertainty. Figure 5 graphs the decrease in the lower trigger point s_1 relative to s_0 for both the baseline depreciation rate and the higher value.

4.4 Varying the Fixed Costs of Ordering

Of course, we expect fixed costs of ordering to be lower when the intermediate input is ordered domestically, i.e., $f_D < f_F$. Figure 6 shows the effect of using the value f_D from above that corresponds to an average interval of 85 days between domestic orders compared to the baseline value f_F in Figure 3. Not surprisingly, the lower the fixed costs of ordering, the bigger the incentive for the firm to keep inventory close to the target level.

Figure 5: The effect of a higher depreciation rate on the decrease in the lower trigger point.

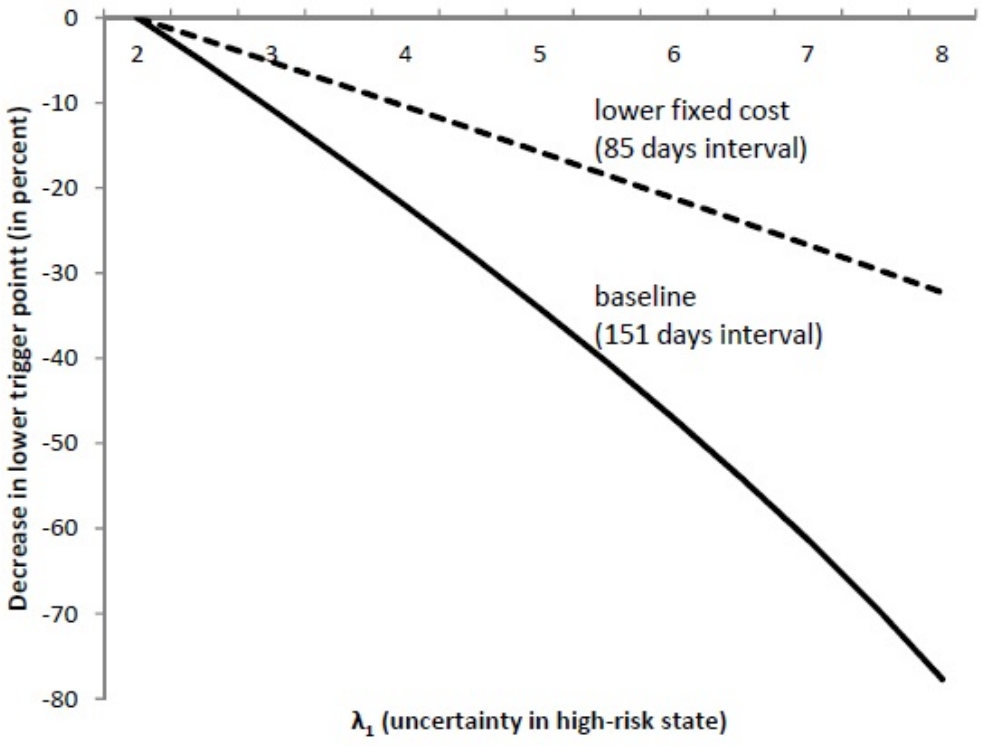


5 Simulating an Uncertainty Shock

So far we have described the behavior of a single firm. We now simulate 50,000 firms that receive shocks according to the stochastic uncertainty process in equations (5) and (6). These shocks are drawn from the same distribution but idiosyncratic for each firm. We use the same parameter values as described in section 4.1. We should add that firms firms do not enter or exit over the simulation period. This assumption seems reasonable given that most of the changes in the value of international trade during the trade collapse of 2008/09 happened at the intensive margin (see Behrens, Corcos and Mion (2012) amongst others). Allowing for extensive margin responses would be an important avenue for future research. We conjecture that the extensive margin would amplify the effect of uncertainty shocks. Firms would be likely to exit in the face of higher uncertainty and likely to enter once the recovery takes hold.

Figure 7 plots the aggregate orders of imported intermediate goods in the economy (normalized to 1 for the average value over time). We simulate a permanent shift from low uncertainty to high uncertainty. Again, we stress that this is purely a second moment

Figure 6: The effect of a lower fixed costs of ordering on the decrease in the lower trigger point.



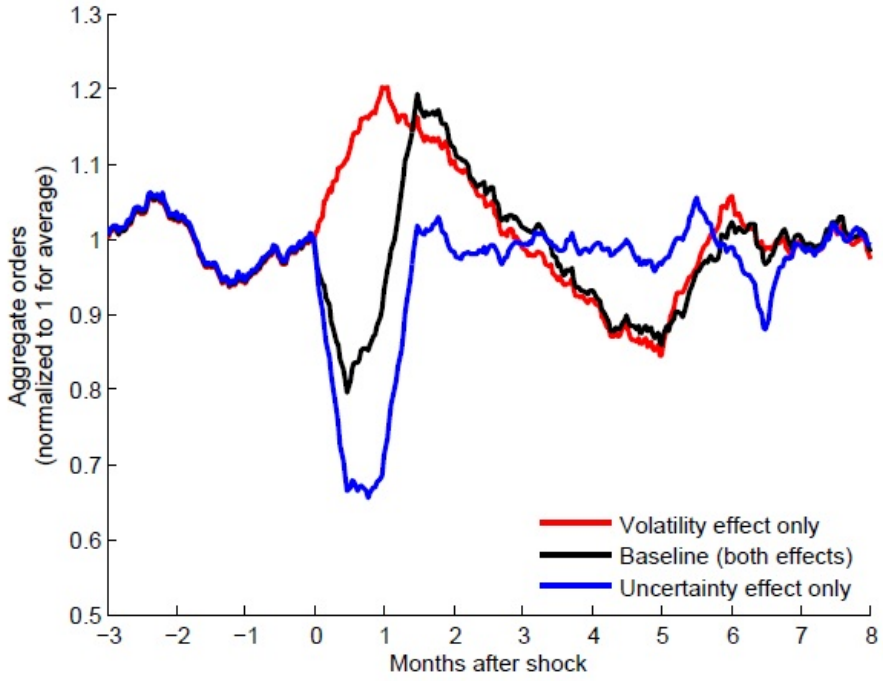
shock, not a first moment shock. Aggregate orders are therefore the same on average before and after the uncertainty shock hits. The reason is that the extent of orders is simply determined by the depreciation rate δ since intermediates depreciate over time.[8]

The black graph in Figure 7 represents the reaction of aggregate orders. They decrease by about 20 percent given our parameterization. The total effect can be decomposed into a 'pure' uncertainty effect (in blue) and a volatility effect (in red). The uncertainty effect is related to the downshifting of the s, S bounds (holding the degree of volatility fixed as implied by λ_0). Once the uncertainty shock hits, firms decrease their lower trigger point such that they initially take longer to run down their inventory. This leads to a sharp drop in orders of imported intermediate inputs. Once firms approach the new lower trigger point, they start restocking. This leads to a sharp recovery in orders. As in Bloom (2009), this pattern of sharp contraction and strong recovery is typical for uncertainty shocks.

The volatility effect is an overshoot caused by the increased probability of firms re-

[8] As firms are equally likely to receive positive or negative shocks, the effects of restocking and destocking cancel on average.

Figure 7: Simulating an uncertainty shock: the total effect decomposed into an uncertainty effect and a volatility effect.

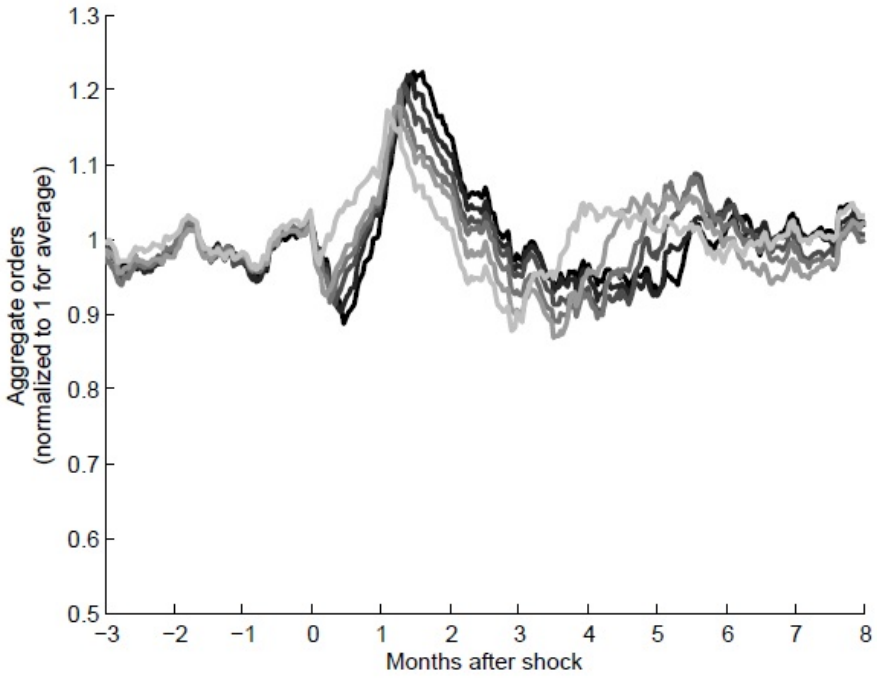


ceiving a shock (holding the s, S bounds fixed). Recall that a shock ε can move output in either direction with equal probability. If a lot of firms are close to the return point, then negative orders (induced by z being pushed above the upper trigger point) and positive orders (induced by z being pushed below the lower trigger point) should be of the same size such that in the aggregate the two cancel (i.e., aggregate orders are close to their average level). However, if a lot of firms have not stocked up in a while (which happens once s falls) so that the average firm is relatively close to the lower trigger point, then the uncertainty shock tends to push up aggregate orders. This effect is analogous to Bloom's (2009) 'volatility overshoot.' The volatility effect only arises in the medium term whereas the uncertainty effect happens immediately.[9]

In Figure 8 we plot the total effect of an uncertainty shock for six different values of fixed costs f. The black line corresponds to the baseline value of $f_F = 0.0000588$.

[9]One implication is that the upper trigger point does not matter for the size of orders. The reason is that the shock size is such that once a shock hits, there is always adjustment (i.e. the upper trigger point is always breached given a shock in the right direction). Therefore, only the return point matters for the size of orders. The lower trigger point also matters to the extent that depreciation runs down a firm's inventory before a shock hits.

Figure 8: Simulating an uncertainty shock for different values of fixed costs of ordering f.



The remaining five lines in grey correspond to declining values of f (with the light grey line corresponding to the smallest value). The values in declining order are 0.00005066, 0.00004066, 0.00003066, 0.00002066 and 0.00001066. The last value corresponds to the domestic fixed cost value above, f_D. The main insight is that although the trade collapse is less severe with smaller fixed cost values (as predicted by the theory), quantitatively the collapse is not as sensitive to fixed costs above a certain threshold. For instance, for the baseline value trade declines to about 88 percent of its average level upon impact of the uncertainty shock. But even with a substantially smaller fixed cost value of $f = 0.0002066$ (which is only about twice as large as the domestic fixed cost value), trade declines to about 92 percent of its average level upon impact. Thus, we may not need f_F to be substantially larger than f_D to generate a strong decline in international trade.

6 Empirical Evidence

To explore the relationship between uncertainty, production, and international trade we run vector autoregressions (VARs) with U.S. data. In particular, we follow the seminal

work of Bloom (2009) in running a VAR to generate an impulse response function (IRF) relating the reactions of key model quantities, in this case not only industrial production but also imports, to the underlying impulses which take the form of shocks to uncertainty.

We contend that, as with the application to production volatility, the payoffs to an uncertainty- based approach will turn out to be substantial again in the new setting we propose for modeling trade volatility. Recall that in the view of Bloom (2009, p. 627):

> More generally, the framework in this paper also provides one response to the "where are the negative productivity shocks?" critique of real business cycle theories. In particular, since second-moment shocks generate large falls in output, employment, and productivity growth, it provides an alternative mechanism to first-moment shocks for generating recessions.

By the same token, the framework in our paper provides one response to the "where are the increases in trade frictions?" objection that is often cited when standard static models are unable to otherwise explain the amplified nature of trade collapses in recessions, relative to declines in output. Our theoretical model, and empirical evidence, can thus be seamlessly integrated with the Bloom (2009) view of uncertainty-driven recessions, whilst matching one other crucial and recurrent feature of international economic experience: the highly magnified volatility of trade, which has been a focus of inquiry since at least the 1930s, and which, since the onset of the Great Recession has flared again as an object of curiosity and worry to scholars and policymakers alike.

6.1 Four Testable Hypotheses

To look ahead and quickly sum up the bottom line, our empirical results expose several new and important stylized facts, all of which are consistent with, and thus can motivate our previously described theoretical framework. Specifically we focus on testing four empirical propositions that would be implied by our theory.

- First, trade volumes do respond to uncertainty shocks, the effects are quantitatively and statistically significant, and are robust to different samples and methods. In addition, trade volumes respond much more to uncertainty shocks than does the volume of industrial production; that is to say, there is something fundamentally different about the dynamics of traded goods supplied via the import channel, as compared to supply originating from domestic industrial production.

- Second, we confirm that these findings are true not just at the aggregate level, but also at the disaggregated level, indicating that the amplified dynamic response of traded goods is not just a sectoral composition effect.

- Third, we find that the dynamic response of traded goods to uncertainty shocks is greatest in durable goods sectors as compared to nondurable goods sectors, consistent with the theoretical model where a decrease in the depreciation parameter (interpreted as an increase in perishability) leads to a larger response.

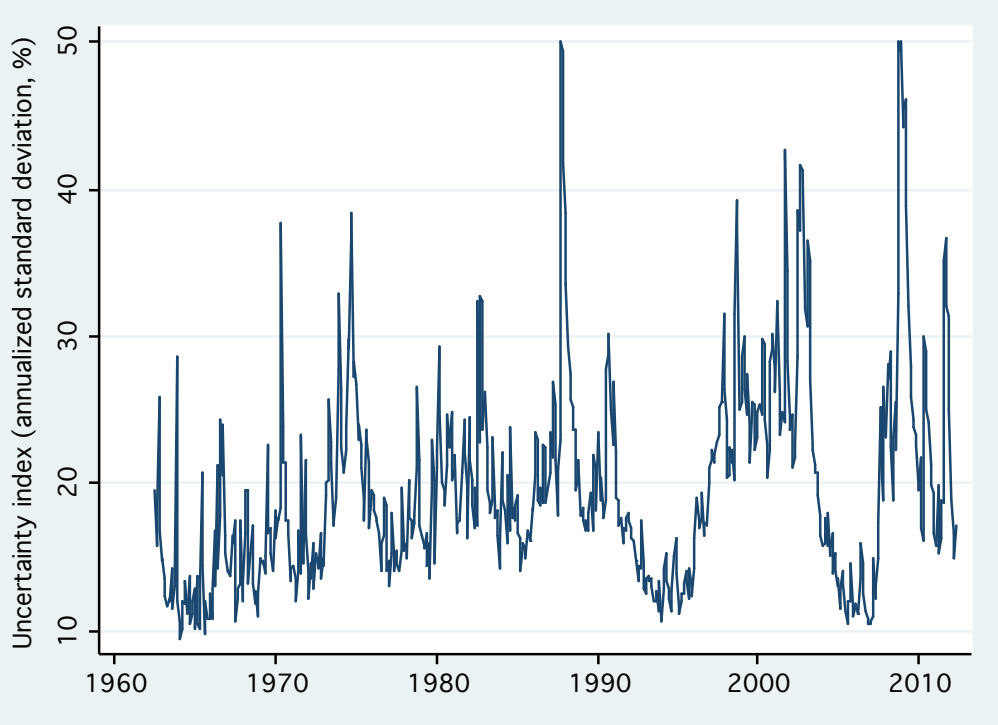
The following six parts of this section are structured as follows. The first part briefly spells out the empirical VAR methods we employ based on Bloom (2009). The second part spells out the data we have at our disposal, some of it newly collected, to examine the differences between trade and industrial production in this framework. The subsequent four parts discuss our findings on the four testable hypotheses noted above.

6.2 Computing the Responses to an Uncertainty Shock

In typical business cycle empirical work, researchers are often interested in the response of key variables, most of all output, to various shocks, most often a shock to the level of technology or productivity. The analysis of such first moment shocks has long been a centerpiece of the macroeconomic VAR literature. The innovation of Bloom (2009) was to construct, simulate and empirically estimate a model where the key shock of interest is a second moment shock, which is conceived of as an "uncertainty shock" of a specific form. This shock amounts to an increase in the variance, but not the mean, of a composite "business condition" disturbance in the model, which can be flexibly interpreted as a demand or supply shock. For empirical purposes when the model is estimated using data on the postwar U.S., Bloom proposes that changes in the market price of the VXO index, a daily options-based implied stock market volatility for a 30-day horizon, be used as a proxy for the uncertainty shock, with realized volatility used when the VXO is not available. A plot of this series, scaled to an annualized form, and extended to 2012, is shown in Figure 9.[10]

[10] As Bloom (2009, Figure 1) notes: "Pre-1986 the VXO index is unavailable, so actual monthly returns volatilities are calculated as the monthly standard deviation of the daily S&P500 index normalized to the same mean and variance as the VXO index when they overlap from 1986 onward. Actual and VXO are correlated at 0.874 over this period. A brief description of the nature and exact timing of every shock is contained in Appendix A. The asterisks indicate that for scaling purposes the monthly VXO was capped at 50. Uncapped values for the Black Monday peak are 58.2 and for the credit crunch peak are 64.4. LTCM is Long Term Capital Management." For comparability, we follow exactly the same definitions here and we thank Nicholas Bloom for providing us with an updated series extended to 2012.

Figure 9: The Bloom (2009) Index: Monthly U.S. stock market volatility, 1962–2012



Source: Bloom (2009) and personal correspondence. See footnote 10.

Following Bloom (2009) we evaluate the impact of uncertainty shocks using VARs on monthly data from June 1962 (the same as in Bloom) to February 2012 (going beyond Bloom's end date of June 2008). Bloom's full set of variables, in VAR estimation order are as follows: log(S&P500 stock market index), stock-market volatility indicator, Federal Funds Rate, log(average hourly earnings), log(consumer price index), hours, log(employment), and log(industrial production).[11]

For simplicity, for the main results of this paper presented in this section, all VARs of this form are estimated using a quad-variate VAR (log stock-market levels, the volatility indicator, log employment, and lastly the industrial production or trade indicator). As with Bloom (2009) an Appendix [to be done] confirms the robustness of our main results to changes in variable ordering, variable inclusion, shock definitions, shock timing, and detrending. In particular, these results are robust to identification from uncertainty shocks

[11]In terms of VAR variable ordering and variable definitions we follow Bloom (2009) exactly for comparability. As Bloom notes: "This ordering is based on the assumptions that shocks instantaneously influence the stock market (levels and volatility), then prices (wages, the consumer price index (CPI), and interest rates), and finally quantities (hours, employment, and output). Including the stock-market levels as the first variable in the VAR ensures the impact of stock-market levels is already controlled for when looking at the impact of volatility shocks."

defined by the 10 exogenous shocks arising from wars, OPEC shocks, and terror events, as with Bloom (2009).

6.3 Data

Many of our key variables are taken from the exact same sources as Bloom (2009). As it is noted: "The full set of VAR variables in the estimation are log industrial production in manufacturing (Federal Reserve Board of Governors, seasonally adjusted), employment in manufacturing (BLS, seasonally adjusted), average hours in manufacturing (BLS, seasonally adjusted), log consumer price index (all urban consumers, seasonally adjusted), log average hourly earnings for production workers (manufacturing), Federal Funds rate (effective rate, Federal Reserve Board of Governors), a monthly stock-market volatility indicator (described below)[above here], and the log of the S&P500 stock-market index. All variables are HP detrended using a filter value of $\lambda = 129,600$." We follow these definitions exactly.

However, in some key respects, our data requirement are much larger than this. For starters, we are interested in assessing the response of trade, so we needed to collect monthly import volume data. In addition, we are interested in computing disaggregated responses of trade and industrial production (IP) in different sectors, in the aftermath of uncertainty shocks, in an attempt to gauge whether some of the key predictions of our theory are sustained. Thus, we needed to assemble new monthly trade data (aggregate and disaggregate) as well as new disaggregated monthly IP data to complement the Bloom data.

We briefly explain the provenance of these newly collected data, all of which will also be HP filtered for use in the VARs as above.

- U.S. aggregated monthly real import volume. These data run from January 1962 to February 2012. After 1989, total imports for general consumption were obtained from the USITC dataweb, where the data can be downloaded online. From 1968 to 1988 data were collected by hand from FT900 reports, where the imports series are only available from 1968 as F.A.S. at foreign port of export, general imports, seasonally unadjusted; the series then change to C.I.F. value available beginning in 1974, and the definition changes to customs value in 1982. Prior to 1968 we use NBER series 07028, a series that is called "total imports, free and dutiable" or else "imports for consumption and other"; for the 1962 to 1967 window this NBER series is a good match, as it is sourced from the same FT900 reports as our hand compiled series. The entire series was then deflated by the monthly CPI.

- U.S. disaggregated monthly real imports. These data only run from January 1989 to February 2012. In each month total imports for general consumption disaggregated at the 4-digit NAICS level were obtained from the USITC dataweb, where the data can be downloaded online. All series were then deflated by the monthly CPI. In this way 108 sector-level monthly real import series were compiled.

- U.S. disaggregated monthly industrial production. These data only run from January 1972 to February 2012 at a useful level of granularity. Although aggregate IP data are provided by the Fed going back to February 1919, the sectorally disaggregated IP data only start in 1939 for 7 large sectors, with ever finer data becoming available in 1947 (24 sectors), 1954 (39 sectors) and 1967 (58 sectors). However, it is in 1972 that IP data are available using the 4-digit NAICS classification which will permit sector-by-sector compatibility with the import data above. Starting in 1972 we use the Fed G.17 reports to compile sector-level IP indices, which affords data on 98 sectors at the start, expanding to 99 in 1986.

6.4 Results 1: IRFs at Aggregate Level for Trade versus IP

We begin with the simplest possible evidence on the importance of uncertainty shocks for trade, using aggregate data on real imports and industrial production.

Following Bloom (2009) exactly, a baseline quad-variate VAR is estimated for both series, which are place last in the ordering. Ordering is stock market, volatility, log employment, followed lastly by either log real imports or log IP. Data differ from Bloom in that we have updated all series through February 2012, so as to include the response to the 2008 financial crisis. However our results are not sensitive to this extension of the sample (see Appendix xxx to be done). The presentation also differs from Bloom in that we do not rescale the IRFs at this stage, since we are only interested in the comparative responses of internationally traded and domestically produced goods.

In Figure 1 we already presented the VAR results for both imports and IP side by side. The impulse response functions (IRFs) are based on a one-period uncertainty shock where the Bloom uncertainty indicator (that is, VXO or its proxy) increases by one unit. The bottom line is very clear from this figure. In response to the uncertainty shock, both industrial production and imports decline. But the response of imports is considerably stronger, about 5 to 10 times as strong in its period of peak impact during year one. The response of imports is also highly statistically significant. At its peak the IRF is 3 or 4 standard errors below zero, whereas the IRF for IP is only just about 2 standard errors below zero, and only just surmounts the 95% confidence threshold.

These results offer prima facie confirmation of the mechanisms suggested in our theoretical model. Indeed to the extent that the Bloom (2009) result for IP has proven novel, robust, and influential, one might argue that our finding of a import response to uncertainty that is almost an order of magnitude larger is also notable, especially since it opens an obvious route towards finding an explanation for the amplification effects seen during the recent trade collapse, a puzzle where, as we have seen, no fully convincing theoretical explanation has yet been given.

However, to make that claim more solid, we must convince the reader that the theoretical mechanisms we propose are indeed at work. To do that, we delve more deeply into the dynamics of disaggregated trade and IP in the wake of uncertainty shocks. The following empirical sections demonstrate that, taking into account cross-sectoral variations in perishability/durability and also in the intensity of downstream intermediate use, the empirical evidence closely matched our model's predictions. We find that imports of any good are, in general, more responsive to uncertainty shocks than domestic IP, whether in broad sectors (like End Use categories), or at a much more disaggregated level (e.g. NAICS 4-digit sectors). However, the aggregate results seen above will be shown to mask substantial sectoral heterogeneity in responses to uncertainty shock. With that taken into account at the end we will be able to weight the responses according, for both imports and IP, and compute a simulated response to the 2008 uncertainty shock aggregated across sectors. We will show that this response closely matches the observed data, with import volume falling about twice as much as a basket of industrial production.

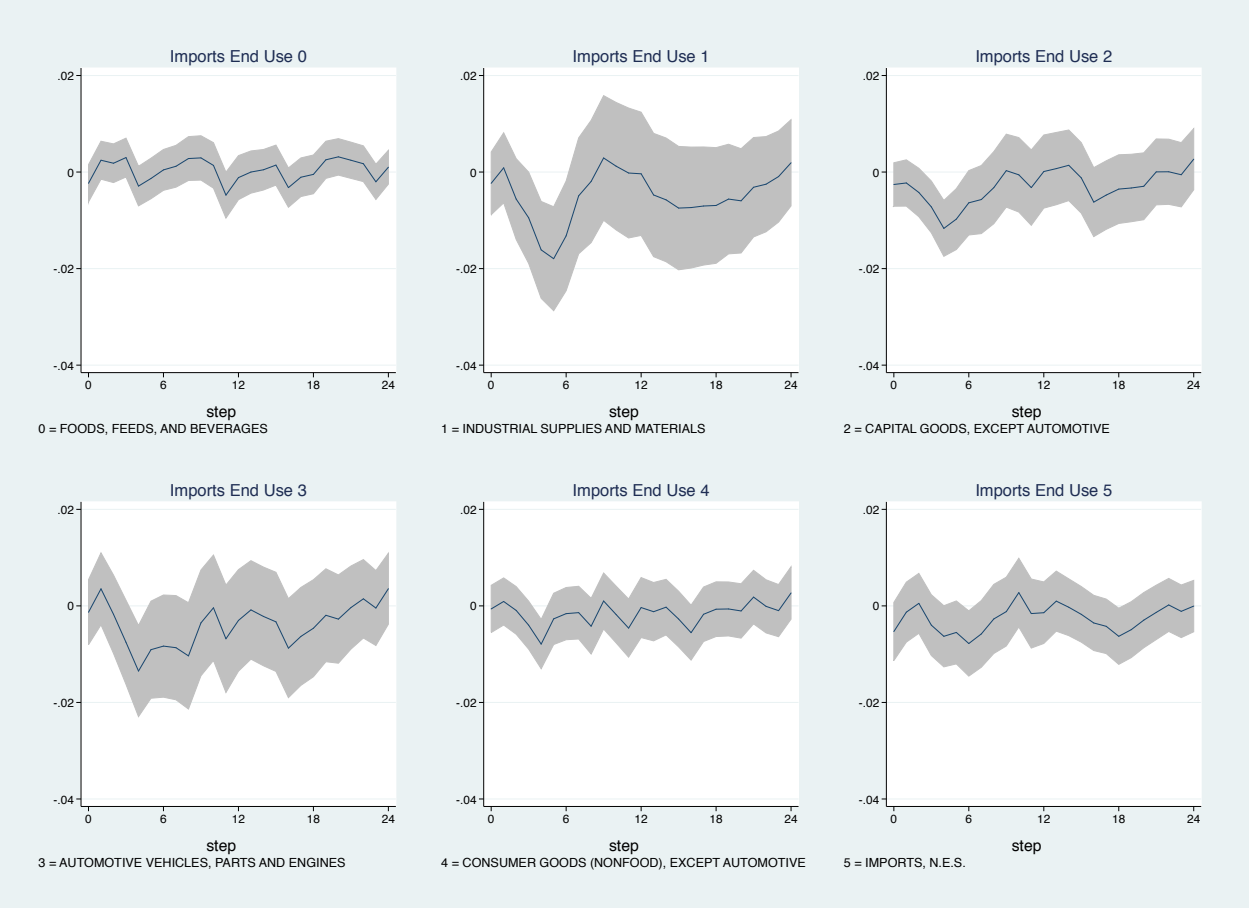
6.5 Results 2: IRFs with Coarse Disaggregation

Proceeding to a coarse level of disaggregation we now investigate IRFs for uncertainty shock when the trade and IP data are divided into either End Use categories (a BEA classification) or into Market Groups (a Fed classification). The purpose is to see whether the aggregate result holds up at the sectoral level, and, to the extent that there is any departure, to see if there is any systematic variation that is yet consistent with our model's more detailed predictions for heterogeneous goods.

Figure 10 shows IRF for real imports disaggregated into 6 BEA 1-digit End Use categories. The response to an uncertainty shock varies considerably across these sectors, but in a manner consistent with some predictions from theory.

There is essentially no response for the most perishable, or least durable, types of goods found in End Use category 0. These goods include foods, feeds and beverages. This response matches up with cases in our model when the depreciation parameter is set very

Figure 10: Import IRFs by End Use category for Uncertainty Shocks



Source: Sample is 1989:1–2012:2. Imports by End Use 1-digit from USITC dataweb, deflated by CPI; all other data as in Bloom (2009), updated. Uncertainty shocks for quadvariate VARs as in Bloom (2009). Ordering is stock market, volatility, log employment, followed lastly by either log real imports or log IP. Data updated through February 2012. No rescaling of shocks. 95% confidence intervals shown. See text.

high. In this case the response to uncertainty shocks diminishes towards zero. Responses are also weak for other nondurable consumer goods (End Use 4) and the residual category of imports not elsewhere specified (End Use 5).

In contrast, some sectors show a very large response to an uncertainty shocks, notably End Use categories 1, 2, and 3, which include industrial inputs, capital goods, and autos. These are all sectors characterized by either high durability and/or high downstream intermediate use. Again, our theory predicts that it is precisely these sectors that will experience the largest amplitude response to an uncertainty shock.

It is not possible to compare these IRFs to the corresponding response of domestic IP using the same End Use classification, since we cannot obtain IP disaggregated by End Use code. However, we can obtain both imports and IP disaggregated in a matched way

at a coarse level by using the Fed's Market Group categories. IP is available directly in this format on a monthly basis and we were able to allocate imports to this classification by constructing a concordance (with some weighting using 2002 data on weights) mapping from 4-digit NAICS imports to Fed Market Group.

Figure 11 shows IRF for real imports (upper panel) and IP (lower panel) disaggregated into Fed Market Group categories. Again, the response to an uncertainty shock varies considerably across these sectors, and we can compare the import and IP responses directly. To facilitate this, all responses are shown on the same scale.

In panel (a) the results for imports are compatible with those above based on the End Use categories. Here, under the Fed Market Groups the largest amplitude responses to an uncertainty shock are seen for materials, business equipment and consumer durables. The responses here are between a 1 and 2 percent drop at peak. The weakest response is for consumer nondurables, which shows about a 0.5 percent drop at the peak, although this is barely statistically significant at the 95% level.

By contrast, in panel (b) the results for IP are very muted indeed. Confidence intervals are tighter, so these responses do in all cases breach the 95% confidence interval within a range of steps. However, the magnitude of the response is qualitatively different from imports. The consumer durables response is just below 1 percent at peak for IP, whereas it had been about twice as large, near 1.5 percent for imports. Materials and business equipment fall at peak by about 0.25 percent for IP, but fell about four times as much in the case of imports. Consumer nondurables in IP are barely perturbed at all.

6.6 Results 3: IRFs with Finer Disaggregation

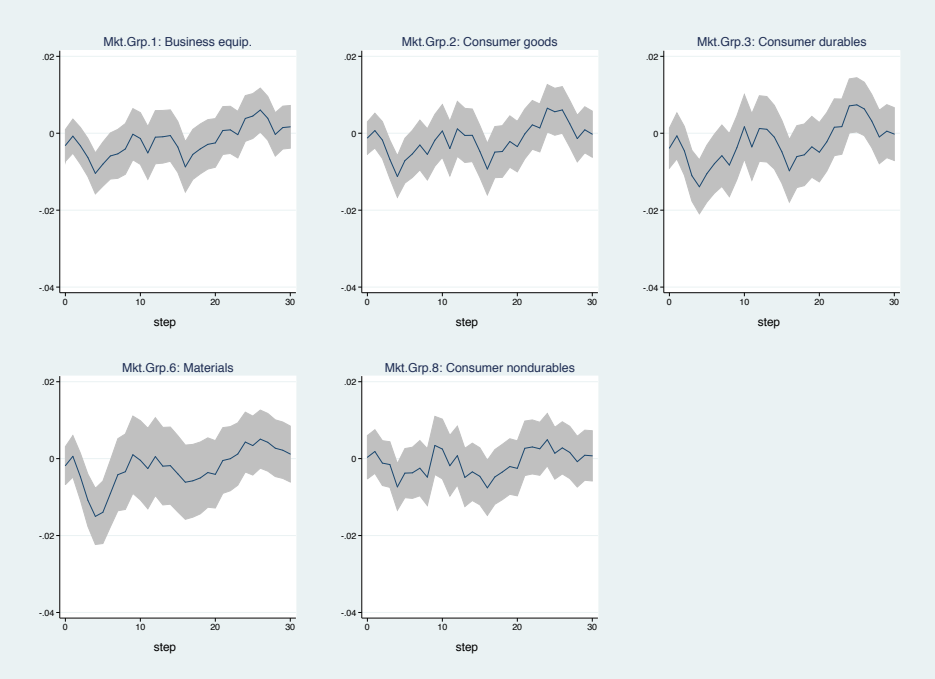
Our final set of results aims to study dynamic responses to uncertainty shocks at an even finer level of disaggregation, whilst still allowing for comparability between import and IP responses. For these purposes we move to the 3- or 4-digit NAICS level of classification, again sourcing the date from USITC dataweb and the Fed G.17 releases at a monthly frequency starting in 1989. The overlap between these two sources allows us to work with 51 individual sectors, as seen in Figure 12.

A similar pattern emerges here, consistent with previous results, whereby the responsiveness in any sector is higher for real imports (CPI deflated) than for industrial production. There are some exceptions but these are generally to be found in only a few sectors. The bars in Figure 12 is ordered from top to bottom starting with largest negative real import response measured by the average sectoral IRF over months 1–12.

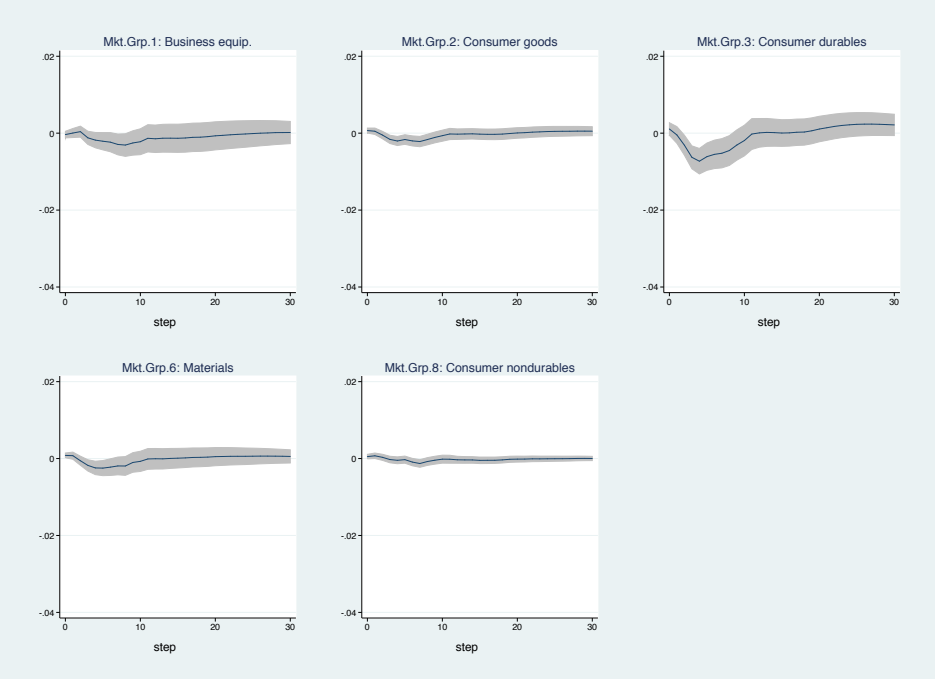
Some of the sectors are also obviously quite peculiar. One is basically a nonmanufac-

Figure 11: Import and IP IRFs by Fed Market Group for Uncertainty Shocks

(a) Real imports

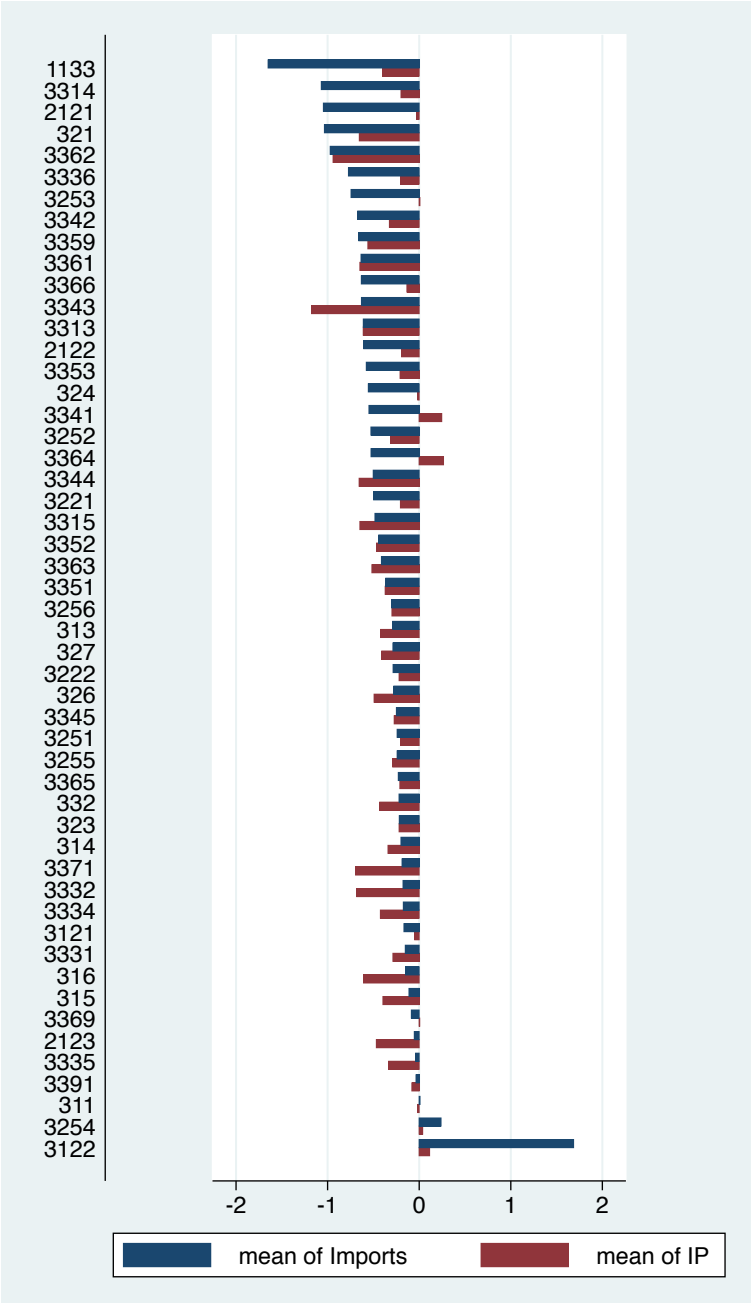


(b) Industrial production



Source: Sample is 1989:1–2012:2. Imports via concordance from USITC dataweb, deflated by CPI; IP from Fed G.17; all other data as in Bloom (2009), updated. Uncertainty shocks for quadvariate VARs as in Bloom (2009). Ordering is stock market, volatility, log employment, followed lastly by either log real imports or log IP. Data updated through February 2012. No rescaling of shocks. 95% confidence intervals shown. See text.

Figure 12: Import and IP IRFs Compared in Months 1–12



Source: Sample is 1989:1–2012:2. Imports from USITC dataweb, deflated by CPI; IP from Fed G.17; all other data as in Bloom (2009), updated. Uncertainty shocks for quadvariate VARs as in Bloom (2009). Ordering is stock market, volatility, log employment, followed lastly by either log real imports or log IP. Data updated through February 2012. No rescaling of shocks. Average IRF for months 1–12. See text.

turing sector, and not very tradable — namely logging (NAICS 1133, which is resource intensive and not highly traded outside imports from Canada). This does fit the general pattern of imports being more volatile than domestic output, but this may reflect downstream use in the heavily procyclical construction industry (we discuss downstream use in the next section). Another oddity is tobacco manufacturing (NAICS 3122), where the response goes heavily against the prevailing pattern, with tobacco imports rising sharply after an uncertainty shock, and domestic supply basically flat. Still, this response is consistent with clinical studies which show that the use of tobacco may rise, and the ability of people to quit smoking may fall, in stressful periods of economic hard times.

Less unusual cases where the negative response of IP exceeds real imports are: Audio and video equipment manufacturing (NAICS 3343); Household and institutional furniture and kitchen cabinet manufacturing (3371); Industrial machinery manufacturing (3332); Ventilation, heating, air-conditioning, and commercial refrigeration equipment manufacturing (3334); Leather and allied product manufacturing (316); Apparel manufacturing (315); Nonmetallic mineral mining and quarrying (2123); Metalworking machinery manufacturing (3335). Still, out of 51 sectors, these are a minority.

But generally, and especially for the high response sectors where responses are significantly different from zero, the real import bar is larger and more negative than the IP bar. The essence of this pattern is revealed in Figure 13 which presents a scatter of the average real import one-year IRF on the vertical axis against the average IP one-year IRF on the horizontal axis. There is only a very weak correlation between these responses (0.25) and when the outlier tobacco sector is excluded the correlation essentially vanishes (it falls to 0.15, but is not statistically significant).

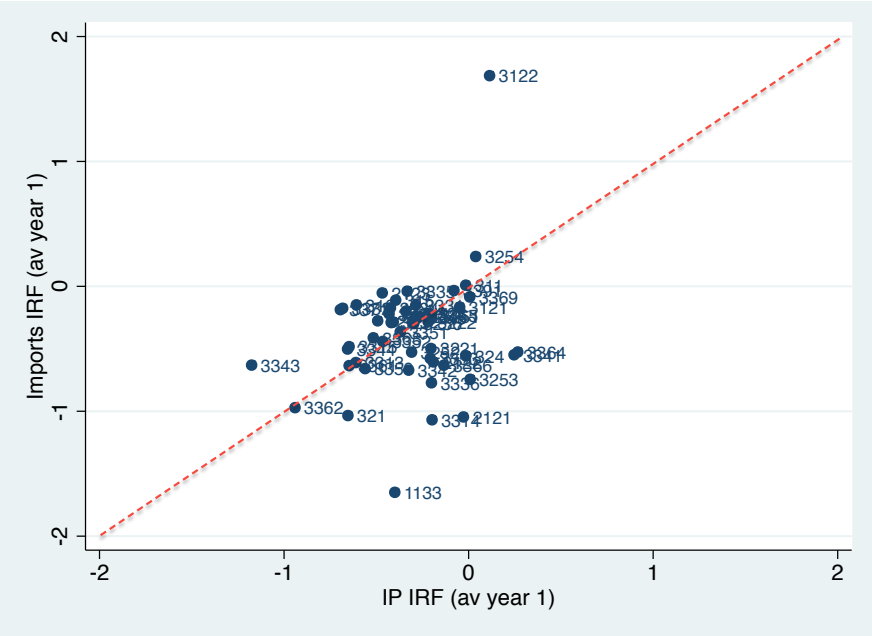
7 Can the Great Trade Collapse Be Explained?

[To be completed.]

The four months following the collapse of Lehman Brothers were characterized by particularly strong increases in uncertainty as measured by the volatility index (Sept.–Dec. 2008). To simulate this shock we observe that the own-response of volatility to itself in the orthogonalized impulse response is about 3. We perturbed the model with four successive +10-unit shocks to volatility, which, given the scaling corresponds to four +30-unit shocks to the VXO index. In actuality, the VXO rose from its pre-crisis mean of about 20 to almost 90 in the last quarter of 2008, and given the decay of the shocks, this set of impulses matches the actual path of VXO quite well, as shown in Figure 14.

Given these shocks he actual aggregate responses to IP and real imports are shown

Figure 13: Import and IP IRFs Compared in Months 1–12



Source: Sample is 1989:1–2012:2. Imports from USITC dataweb, deflated by CPI; IP from Fed G.17; all other data as in Bloom (2009), updated. Uncertainty shocks for quadvariate VARs as in Bloom (2009). Ordering is stock market, volatility, log employment, followed lastly by either log real imports or log IP. Data updated through February 2012. No rescaling of shocks. Average IRF for months 1–12. See text. *Notes*: The correlation of the two variables is 0.2544 (with a significance level of $p = .0716$). However, the correlation falls to 0.1467 and is not statistically significant ($p = .3092$) when tobacco (3122) is excluded. What is more striking in the figure, however, is the general asymmetry relative to the 45 degree line. Most points lie in the lower-left quadrant where both real imports and IP react negatively to an uncertainty. In that quadrant, we do find points above the diagonal, where the IP response is more negative than the real import response – but generally these deviations from the diagonal are small. In contrast several sectors fall well below the diagonal by a significant margin, indicating a much sharper negative response of real imports compared to IP.

in Figure 15. As can be seen the IRF for IP is capable of explaining a large fraction of actual observed IP response. But it is wholly incapable of explaining the real import response. Our simulations can explain about 75-80 percent of the subsequent imports collapse. But especially in the first quarter of 2009, additional factors must be at work that are not captured by heightened uncertainty. Nonetheless, this shows that the evidence is consistent with a large fraction of the Trade Collapse being explicable in terms of second moment uncertainty shocks, rather than the conventional first moment explanations.

Figure 14: Actual and simulated VXO, Aggregate Model

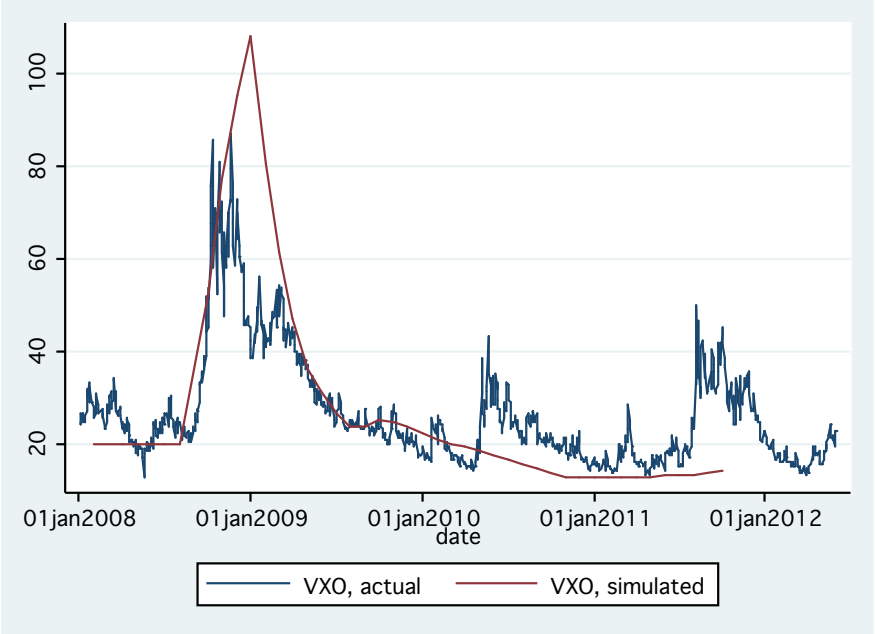
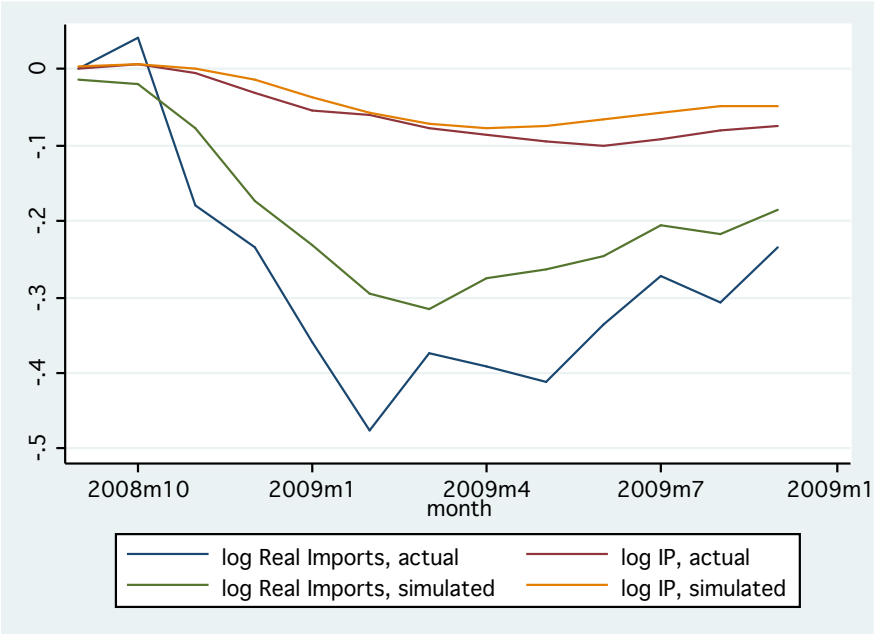


Figure 15: Actual and simulated Real Imports and IP, Aggregate Model



8 Conclusion

Following the seminal paper by Bloom (2009), we introduce uncertainty shocks into a dynamic, open-economy model of international trade. Firms import intermediate inputs and due to a fixed costs of ordering store them according to an optimal s, S inventory policy. We adapt the inventory model by Hassler (1996) to show that elevated uncertainty leads to sharp trade contractions followed by swift recoveries. Uncertainty shocks can explain why trade is more volatile than domestic economic activity.

Our results offer an explanation for the Great Trade Collapse of 2008/09 in a way that differs from the conventional static trade models or dynamic inventory models seen before. We argue that imports and IP can be modeled as reacting to uncertainty shocks in theory and in practice. Such second moment shocks are needed since the required first moment shocks are either absent on the impulse side or insufficient on the propagation side (for plausible parameters) to explain the events witnessed. However, theory suggests and empirical analysis confirms, that real imports react much more to uncertainty shocks than IP. We can also show that there is substantial heterogeneity in responses at the sectoral level, both for imports and IP, in a way consistent with the model.

[To be completed.]

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9 Technical Appendix

[Characterize the upper trigger bound.]

[Add the steps for solving the time-varying uncertainty model.]

[As Hassler (1996, p. 1121) notes, the normalized bandwidth $\frac{S-s}{\delta}$ equals the time it takes capital to depreciate from the return point S to the lower trigger point s if no shocks occur. To see this, let $K_S = \exp(S)$ denote the level of capital at the return point and $K_s = \exp(s)$ the level at the lower trigger point. Given the depreciation rate δ it follows $K_s = K_S \exp(-\delta t)$. Solving for t yields $t = \frac{S-s}{\delta}$.]

[Add a table with a list of NAICS 4-digit codes as used in Figure 13. See source for 4-digit NAICS codes here: http://reportweb.usitc.gov/commodities/naicsicsitc.html]