

Trade and Uncertainty*

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Abstract

We offer a new explanation as to why international trade is so volatile in response to economic shocks. Our approach combines the idea of uncertainty shocks with international trade. In an open economy framework, firms order inputs from home and foreign suppliers, but with higher costs in the latter case. Due to fixed costs of ordering firms hold an inventory of inputs. In response to an uncertainty shock firms optimally adjust their inventory by cutting orders of foreign inputs disproportionately strongly. In the aggregate, this leads to a bigger contraction in international trade flows than in domestic activity, a magnification effect. We confront the model with newly-compiled U.S. import data and industrial production data going back to 1962, and also with disaggregated data at the industry level back to 1989. Our results suggest a tight link between uncertainty and fluctuations in international trade.

Keywords: Industry, imports, inventory, real options, trade collapse, uncertainty shock

JEL Codes: E3, F1

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1. INTRODUCTION

The recent global economic crisis saw an unusually large and rapid decline in output across the world. Yet, even more striking, the accompanying decline in international trade volumes was sharper still, and almost twice as big. Globally, industrial production fell 12% and trade volumes fell 20% in the 12 months from April 2008, shocks of a magnitude not witnessed since the Great Depression (Eichengreen and O'Rourke 2010). Just as the causes of the trade collapse in the 1930s are hotly disputed to this day, so too, we think, the recent reprise will be an object of debate by economists for years to come. Why? Already one clear reason stands out, which is that standard, extant models of international trade and macroeconomics fail to account for the severity of the events in 2008–09 now known as the Great Trade Collapse.

As we shall explain in the next section of the paper, it is quite easy for these models—based on standard first-moment shocks, which we do not deny are clearly in operation—to explain why trade falls in proportion to output, or demand. But, without the addition of auxiliary arguments based on the composition of trade—plus a theory as to why some components fall disproportionately—such models cannot easily explain why trade typically falls roughly twice as much as GDP in massive downturn episodes like the post-2008 years or the early 1930s.

In this paper, we attempt to explain why, international trade is so much more volatile in response to economic shocks. And rather than assuming composition effects, we provide a theory as to why some components of trade are more volatile than others. On the theoretical side, we combine the uncertainty shock concept due to Bloom (2009) with a model of international trade. This 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 shows that bouts of heightened uncertainty can be modeled as *second-moment* shocks to demand or productivity and that these events 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 bring the uncertainty shock approach into an open economy. Unlike the previous closed-economy set-up, ours is a theoretical framework in which firms import nondurable ('material') and durable ('capital') inputs from foreign and domestic suppliers. This structure is motivated by the observation that a large fraction of international trade now consists of goods such as industrial machinery or capital goods, a feature of the global production system which has taken on increasing importance in recent decades.¹

In the model we develop, due to fixed costs of ordering associated with transportation, firms hold an inventory of inputs but the ordering costs are larger for foreign inputs. Following the inventory model with time-varying uncertainty by Hassler (1996), we show that in response to a large uncertainty shock in business conditions, whether to productivity or the demand for final products, firms will optimally execute their inventory policy by cutting orders of foreign inputs much more than for domestic inputs. Hence, in the aggregate, this differential response leads to a bigger contraction and subsequently a stronger recovery in international trade than in domestic trade—that is, trade exhibits more volatility. In a nutshell, uncertainty shocks magnify the response of international trade, given the differential cost structure.

¹See, e.g., Campa and Goldberg (1997); Feenstra and Hanson (1999); Eaton and Kortum (2001); Engel and Wang (2011). The World Bank WITS database reports that in 2014, capital goods made up 31% of global trade, compared to 33% for consumer goods, 21% for intermediate goods and 11% for raw materials. Levchenko, Lewis, and Tesar (2010) stress that sectors with goods used as intermediate inputs experienced substantially bigger drops in international trade during the Great Recession. Likewise, Bems, Johnson, and Yi (2011) confirm the important role of trade in intermediate goods.

This is a new prediction which has never been tested before, or even proposed, but we show that it is matched by the data. On the empirical side, we confront the model with high-frequency monthly U.S. import and industrial production data, some of it new and hand-collected, going back to 1962. Our results suggest a tight link between uncertainty shocks and the cyclical behavior of international trade when we employ an identical VAR empirical framework to the one pioneered by Bloom (2009) but applied here to trade as well as output data. Specifically, we find that imports respond negatively, and in a statistically significant way, and more than output, when there is a shock to a standard uncertainty measure, the VXO stock market option-implied volatility index.

We can further show that our proposed model generates a wider array of additional and original testable predictions, which we also take to the data and test in this paper. The magnification effect should be muted for industries characterized by high depreciation rates. Nondurable goods are a case in point. The fact that such goods have to be ordered frequently means that importers have little choice but to keep ordering them even if uncertainty rises. Conversely, durable goods can be seen as representing 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 is 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 uncertainty shocks using U.S. disaggregated monthly trade data, also a first result of its kind.

We stress that the magnification effect is in operation within industries, by varying extent as predicted by the model. Using disaggregated data we find that the effect is strongest in the durable and capital goods sectors, and weak to nonexistent in other sectors. Our results are therefore not driven by composition effects—that is, they arise not merely from the fact that international trade is more heavy in durable goods.

To wrap up, we show how our proposed mechanism helps to quantitatively explain

a part of the Great Trade Collapse of 2008–09. We use the VAR model in a simulation exercise and impose shocks that reproduce the exceptional rise in uncertainty in 2008 (from the subprime crisis to the collapse of Lehman Brothers). Using standard Cholesky ordering to ensure identification of the response in the trade equation to an uncertainty shock, whilst simultaneously controlling for first-moment shocks to business conditions proxied by employment, we show empirically that second-moment shocks have a sizeable and independent effect on trade. The result holds also for just the exogenous shocks (terror/war/oil) identified by Bloom (2009). Crucially, using disaggregated data, we can show that these uncertainty effects are concentrated in exactly the traded sectors needed to match the compositional variation seen in the trade collapse. The results suggest that if we place a lot of emphasis on uncertainty shocks, up to one-half of the unusually large decline in trade in 2008–09 was in response to this spike in uncertainty.²

Thus, although it stands out quantitatively, the recent downturn is qualitatively quite comparable to previous postwar contractions in international trade and can be modeled similarly. In fact, we think that our approach may advance our understanding of trade contractions and volatility over the long run, not only during the Great Trade Collapse.

The paper is organized as follows. In section 2 we review the literature. In sections 3, 4 and 5 we outline our theoretical model, do comparative statics, and present simulation results. Section 6 presents our empirical evidence. In section 7 we ask to what extent uncertainty shocks can empirically account for the recent Great Trade Collapse. Section 8 concludes. We also provide a detailed online appendix.

²Similarly, Bloom, Bond and Van Reenen (2007) provide empirical evidence that fluctuations in uncertainty can lead to quantitatively large adjustments of firms' investment behavior.

2. THE LITERATURE ON THE GREAT TRADE COLLAPSE

Departing from conventional static trade models, such as those based on the gravity equation, our paper focuses on the dynamic response of international trade. The novelty is that shocks to the volatility of idiosyncratic disturbances, i.e., second-moment shocks, can be the driver of very different changes in imported and domestic inputs. Previous theoretical and empirical work has almost exclusively focused on first-moment shocks, e.g., to productivity, exchange rates, or trade costs. Our approach is relevant for researchers and policymakers alike who seek to understand the crash and recovery process in response to the Great Recession, and may also be relevant for understanding historical events like the 1930s Great Depression. It could also help account for the response of international trade in future economic crises.

We are not the first authors to consider uncertainty and real option values in the context of international trade, but so far the literature has not focused on *uncertainty shocks*. For example, Baldwin and Krugman (1989) adopt a real options approach to explain the hysteresis of trade in the face of large exchange rate swings but their model only features standard first-moment shocks. More recently, the role of uncertainty has attracted new interest in the context of trade policy and trade agreements (Handley 2014; Handley and Limão 2015; Limão and Maggi 2015). Closer to our approach, in independent and contemporaneous work Taglioni and Zavacka (2012) empirically investigate the relationship between uncertainty and trade for a panel of countries using quarterly as opposed to monthly data. But they do not provide a theoretical mechanism, and do not speak to variation across industries.³

³Whilst Bloom (2009) considers U.S. domestic data, Carrière-Swallow and Céspedes (2013) consider domestic data on investment and consumption across 40 countries and their response to uncertainty shocks. Gourio, Siemer and Verdelhan (2013) examine the performance of G7 countries in response to heightened volatility. None of these papers

The Great Trade Collapse of 2008–09 has been documented by many authors (see Baldwin 2009 for a collection of approaches, and Bems, Johnson, and Yi 2013 for a survey). Eaton, Kortum, Neiman, and Romalis (2016) develop a structural model of international trade where the decline in trade is attributed to various combined first-moment shocks, in particular a decline in the efficiency of investment in durable manufactures, a collapse in the demand for tradable goods, and an increase in trade frictions.⁴ They find that the first explains the majority of declining trade. Our approach is different in that the collapse in demand is generated by a second-moment uncertainty shock, and we can endogenize the differential response across sectors. Firms react to the uncertainty by adopting a ‘wait-and-see’ approach, and we do not require first-moment shocks or an increase in trade frictions to account for the excess volatility of trade.

Our approach is consistent with the view that trade frictions did not materially change in the recent crisis. Evenett (2010) and Bown (2011) find that protectionism was contained during the Great Recession. This view is underlined by Bems, Johnson, and Yi (2013). More specifically, Kee, Neagu, and Nicita (2013) find that less than two percent of the Great Trade Collapse can be explained by a rise in tariffs and antidumping duties. Bown and Crowley (2013) find that, compared to previous downturns, during the Great Recession governments notably refrained from imposing temporary trade barriers against partners who experienced economic difficulties.

Works by 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

consider international trade flows.

⁴Leibovici and Waugh (2019) show that the increase in implied trade frictions can be rationalized by a model with time-to-ship frictions such that agents need to finance future imports upfront (similar to a cash-in-advance technology) and become less willing to import in the face of a negative income shock.

of uncertainty on investment cannot be explained by liquidity constraints. We do not incorporate credit frictions here, but such mechanisms may be complementary to our approach and we do not rule out a role for other mechanisms.

As Engel and Wang (2011) point out, 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. In contrast, we relate the excess volatility of trade to inventory adjustment in response to uncertainty shocks. As this mechanism applies *within* an industry, compositional effects do not drive the volatility of international trade in our model.

Our paper is also related to works by Alessandria, Kaboski, and Midrigan (2010a; 2011) who rationalize the decline in international trade by changes in firms' inventory behavior driven by a first-moment supply shock and procyclical inventory investment (Ramey and West 1999). In contrast, we focus on the role of increased uncertainty when second-moment shocks are the driver of firms' inventory adjustments. In our U.S. data, heightened uncertainty stands out as a defining feature of the Great Recession, and we employ an observable measure of it. On the other hand, as we show, there is little evidence in the U.S. data of a major first-moment TFP shock coincident with the onset of the crisis.

Last but not least, Alessandria, Choi, Kaboski and Midrigan (2015) model second-moment shocks but their framework does not have inventory. As far as we are aware, ours is the first paper to jointly model inventory holdings and uncertainty shocks in one framework. Unlike in our paper, a second-moment shock in Alessandria et al. (2015) is a shock to the variance of the heterogeneous productivity distribution. They find that trade rises in response to a second-moment shock. This result is driven by the differential impact of the rising productivity dispersion on exporters vs. non-exporters. Intuitively, exporters tend to be in the upper tail of the productivity distribution. Increases in the dispersion of productivity shocks thus confer an even greater advantage to exporters

compared to non-exporters.⁵ This is different from our setting where the probability of getting hit by a shock changes symmetrically for all firms, and trade falls in response to a second-moment shock.

3. A MODEL OF TRADE WITH UNCERTAINTY SHOCKS

We adopt Hassler's (1996) setting of investment under uncertainty and embed it into a model of trade in capital inputs. 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 setup, we model 'investment' as firms' investing in inventory of capital inputs required for production. Due to fixed costs of ordering firms build up an inventory that they run down over time and replenish at regular intervals. Some inputs are ordered domestically, and others are imported from abroad. Thus, we turn the model into an open economy.

In addition, firms will face uncertainty over 'business conditions' (using Bloom's terminology), which means they experience unexpected fluctuations in productivity and/or 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.

⁵As Alessandria et al. (2015) recognize, they uncover "a puzzle for the standard business cycle model used to understand micro-level trade dynamics: Increases in firm-level dispersion lead to large increases in trade rather than the steep declines typically observed during recessions."

3.1. Production and Demand

Each firm has a Cobb-Douglas production function

$$F(A, K_D, K_F) = AK_D^\alpha K_F^{1-\alpha}, \quad (1)$$

where A is productivity, K_D is a capital input sourced domestically and K_F is a capital input sourced from foreign suppliers. We assume that K_D and K_F are differentiated through the Armington assumption so that firms need to import both types. These capital inputs depreciate at rate δ (so ‘durable’ would map to low δ , ‘nondurable’ to high δ). Each firm faces isoelastic demand Q for its output, with elasticity σ , so that

$$Q = BP^{-\sigma}, \quad (2)$$

where B is a demand shifter. As we focus on the firm’s short-run behavior, we assume that the firm takes the prices of the production factors as given and serves the demand for its product.⁶ We thus adopt a partial equilibrium approach to keep the model tractable.

⁶We 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 nondurables) hardly changed during the Great Trade Collapse of 2008–09. They conclude that the sharp decline in the value of international trade in differentiated goods was “almost entirely a quantity phenomenon.” In contrast, prices of non-differentiated manufactures decreased considerably. In the empirical part of the paper, however, we most heavily rely on differentiated products. For a sample that also includes non-US countries, Haddad, Harrison and Hausman (2010) find some evidence of rising manufacturing import prices, consistent with the hypothesis of supply side frictions such as credit constraints.

3.2. Inventory and Trade

The factors K_D and K_F are capital inputs, say, specialized machinery from domestic and foreign suppliers. Later on, in our empirical trade and production data at the 4-digit industry level, examples include ‘electrical equipment’, ‘engines, turbines, and power transmission equipment’, ‘communications equipment,’ and ‘railroad rolling stock.’ We can consider the firm described in our model as ordering a mix of such products.⁷

Since the inputs depreciate, the firm has to reorder them once in a while. As the firm has to pay a fixed cost of ordering per shipment, it stores the inputs as inventory and follows 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. Ordering inputs leads to domestic trade flows and imports, respectively. We assume that ordering foreign inputs is associated with higher fixed costs compared to domestic inputs, $0 < f_D < f_F$. This assumption is consistent with evidence by Kropf and Sauré (2014) who show that fixed costs per shipment are strongly correlated with shipping distance, and they are substantially higher between countries speaking different languages and not sharing a free trade agreement. Otherwise, we treat the two types of fixed costs in the same way.⁸

Given the input prices, the Cobb-Douglas production function (1) implies that the firm’s use of K_D and K_F is proportional to output Q regardless of productivity and demand fluctuations. Similar to Hassler (1996) we assume that the firm has target levels

⁷This setup is related to a situation where inventories are seen as a factor of production (Ramey 1989).

⁸Guided by the empirical evidence on the importance of adjustment through the intensive margin (Behrens, Corcos, and Mion 2013; Bricongne, Fontagné, Gaulier, Taglioni, and Vicard 2012), we do not model firms’ switching from a foreign to a domestic supplier, or vice versa. As we discuss in section 5, this would arguably reinforce the negative impact of uncertainty shocks on imports.

of inputs to be held as inventory, denoted by M_D^* and M_F^* , which are proportional to both Q as well as K_D and K_F , respectively. Thus, we can write

$$m_D^* = c_D + q, \tag{3}$$

where c_D is a constant, $m_D^* \equiv \ln(M_D^*)$ denotes the log inventory target, and $q \equiv \ln(Q)$ denotes log output. Grossman and Laroque (1990) show that such a target level can be rationalized as the optimal solution to a consumption problem in the presence of adjustment costs.⁹ In our context the target level can be similarly motivated if it is costly for the firm to adjust its level of production up or down. An analogous equation holds for m_F^* but, for simpler notation, we drop the D and F subscripts from now on.

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 m^* as $\frac{1}{2}z^2$ with $z \equiv m - m^*$. Note that the loss function is specified in logarithms such that when expressed in levels, negative deviations from the target are relatively more costly. Losses associated with negative deviations could be seen as the firm's desire to avoid a stockout. Losses associated with positive deviations could be seen as a desire to avoid excessive storage costs. We refer to the theory appendix where we discuss stockout avoidance in more detail and introduce an asymmetric loss function based on Elliott, Komunjer and Timmermann (2005).

Clearly, in the absence of ordering costs, the firm would choose to continuously set m equal to the target m^* , with zero deviation. However, since we assume positive ordering

⁹In their model consumers have to decide how much of a durable good they should hold given that they face fluctuations in their wealth. Adjustment is costly due to transaction costs. Under the assumption of the consumers' utility exhibiting constant relative risk aversion, the optimal amount of the durable good turns out to be proportional to their wealth.

costs ($f > 0$), the firm faces a trade-off: balancing the fixed costs on the one hand and the costs of deviating from the target on the other. Changes in inventory are brought about whenever the firm pays the fixed costs f to adjust m .¹⁰

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 in the following way: when the 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 $S = s + \phi$.¹¹ Formally, we can state the problem as follows:

$$\min_{\{I_t, z_t\}_0^\infty} \left\{ E_0 \int_0^\infty e^{-rt} \left(\frac{1}{2} z_t^2 + I_t f \right) dt \right\} \quad (4)$$

subject to

$$\begin{aligned} z_0 &= \bar{z}; \\ z_{t+dt} &= \begin{cases} \text{free} & \text{if } m_t \text{ is adjusted,} \\ z_t - \delta dt - dq & \text{otherwise;} \end{cases} \\ I_t dt &= \begin{cases} 1 & \text{if } m_t \text{ is adjusted,} \\ 0 & \text{otherwise.} \end{cases} \end{aligned}$$

I_t is a dummy variable that takes on the value 1 whenever the firm adjusts m_t by paying f , $r > 0$ is a constant discount rate, and $\delta > 0$ is the depreciation rate for the input so that $dK_t/K = \delta dt$. Note that the input only depreciates if used in production, not if it is

¹⁰As an alternative interpretation, we could also regard the firm's problem as a capital investment problem. The firm faces a fixed adjustment cost due to the ordering costs and a quadratic penalty for deviating in investment from the target. This interpretation is more closely in line with Engel and Wang (2011).

¹¹That is, in full notation, we have s_D, S_D, ϕ_D for domestic inputs and s_F, S_F, ϕ_F for foreign inputs.

merely in storage as inventory.

3.3. Business Conditions with Time-Varying Uncertainty

Due to market clearing, output can move due to shifts in productivity A in equation (1) or demand B in equation (2). We refer to the combination of supply and demand shifters 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 and $\lambda > 0$, q shifts up or down by the amount ε :

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

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 m^* . Following Hassler (1996) we assume that ε is sufficiently large such that it becomes optimal for the firm to adjust m .¹² That is, a positive shock to output increases m^* sufficiently to lead to a negative deviation z that reaches below the lower trigger point s . As a result the firm restocks m . Vice versa, a negative shock reduces m^* sufficiently such that z reaches above the upper

¹²Hassler (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. Choosing different values for ε does not affect our simulation results in section 5 as long as ε is sufficiently large to trigger adjustment. The reason is that in the aggregate across many firms, the idiosyncratic shocks wash out to zero. We note that the shock is permanent, but the frequency with which the firm gets hit by the shock is subject to a stochastic transition process as given in expression (6). We are not aware of evidence in this context as to whether firms get predominantly hit by transitory or permanent shocks.

trigger point and the firm destocks m .¹³ Thus, to keep our model tractable we allow the firm to both restock and destock depending on the direction of the shock.

The process (5) has a *first moment* equal to zero and constant, independent of ε . In what follows, we hold ε fixed. Thus, the arrival rate of shocks λ is the main measure of uncertainty and will be our key parameter of interest. It determines the *second moment* of shocks. 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. Higher uncertainty here does not mean an increased probability of larger shocks.

Specifically, as the simplest possible set-up, we follow Hassler (1996) by allowing an indexed level of 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

$$\omega_{t+dt} = \begin{cases} \omega_t & \text{with probability } 1 - \gamma_\omega dt, \\ \bar{\omega}_t & \text{with probability } \gamma_\omega dt, \end{cases} \quad (6)$$

where $\bar{\omega}_t = 1$ if $\omega_t = 0$, and vice versa. The probability of switching the uncertainty state in the next instant dt is therefore $\gamma_\omega dt$, with the expected duration until the next switch given by γ_ω^{-1} .

Below, when we calibrate the model, 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.¹⁴ We assume the firm knows the parameters of the stochastic process described

¹³To keep the exposition concise we do not explicitly describe the upper trigger point, and focus on the lower trigger point s and the return point S . But it is straightforward to characterize the upper trigger point.

¹⁴Overall, the stochastic process for uncertainty is consistent with Bloom's (2009). In his setting uncertainty also switches between two states (low and high uncertainty) with given transition probabilities. But he models uncertainty as the time variation of the

by (5) and (6) and takes them into account when solving its optimization problem (4).

The theory appendix shows how the Bellman equation for the inventory problem can be set up and how the system can be solved. We have to use numerical methods to obtain values for the four main endogenous variables of interest: the bounds s_0 and S_0 for the state of low uncertainty λ_0 , and the bounds s_1 and S_1 for the state of high uncertainty λ_1 .

4. TIME-VARYING UNCERTAINTY AND FIRM INVENTORY BEHAVIOR

The main purpose of this section is to explore how the firm endogenously changes its s, S bounds in response to increased uncertainty. Our key result is that the firm *lowers* the 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 just explained, the model cannot be solved analytically, so we use numerical methods.

4.1. Parameterizing the Model

We choose the same parameter values for the interest rate and rate of depreciation as Bloom (2009), i.e., $r = 0.065$ and $\delta = 0.1$ per year. The interest rate value corresponds to the long-run average for the U.S. firm-level discount rate. Based on data for the U.S. manufacturing sector from 1960 to 1988, Nadiri and Prucha (1996) estimate depreciation rates of 0.059 for physical capital and 0.12 for R&D capital. As reported in their paper, those are somewhat lower than estimates by other authors. We therefore take $\delta = 0.1$ as a reasonable baseline, although NIPA-based estimates are usually lower.

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 uncertainty shock has an average half-life of 2 months. This information can be expressed in terms of the transition probabilities in equation (6)

volatility of a geometric random walk.

with the help of a standard process of exponential decay for a quantity D_t :

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

Setting t equal to $2/12$ years yields a rate of decay $g = 4.1588$ 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. We can then compute the average length of time that an element remains in the set. This is the mean lifetime of the decaying quantity, and it is simply given by g^{-1} . It corresponds to the expected duration of the high-uncertainty state, γ_1^{-1} , which is then given by $4.1588^{-1} = 0.2404$ years (88 days) with $\gamma_1 = g = 4.1588$.

Bloom (2009) furthermore reports a frequency of 17 uncertainty shocks in 46 years. Hence, an uncertainty shock arrives on average every $46/17 = 2.7059$ years. Given the duration of high-uncertainty periods from above, in our model this would imply an average duration of low-uncertainty periods of $2.7059 - 0.2404 = 2.4655$ years. It follows from this that $\gamma_0 = 2.4655^{-1} = 0.4056$.

The uncertainty term λdt in the marked point process (5) indicates the probability that output is hit in the next instant by a supply or demand shock that is sufficiently large to shift the target level of inventory. Thus, the expected length of time until the next shock is λ^{-1} . 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 $\lambda_0 = 1$, which implies that the target level of inventory is adjusted on average once a year. This value can therefore be interpreted as an annual review of inventory policy.

However, we point out here that our results are not particularly sensitive to the λ_0 value. In our baseline specification we follow Bloom (2009, Table II) by doubling the standard deviation of business conditions in the high-uncertainty state. This corresponds to $\lambda_1 = 4$.¹⁵ In the comparative statics below we also experiment with other values for λ_1 . An uncertainty shock is defined as a sudden shift from λ_0 to λ_1 , with the persistence of

¹⁵For a given λ , the conditional variance of process (5) is proportional to λ so that the

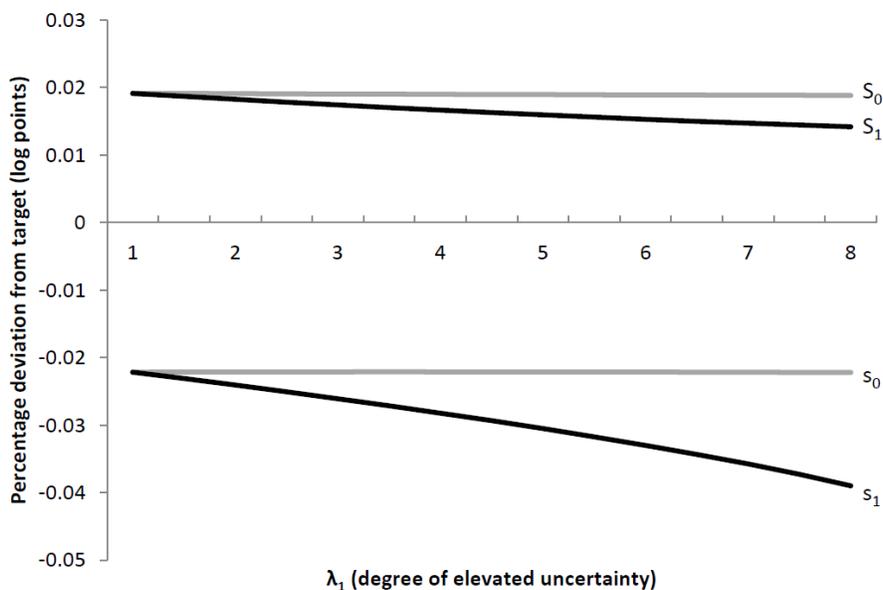
the high-uncertainty state implied by γ_1 .

Finally, we need to find an appropriate value for the fixed costs of ordering, f_F and f_D . Based on data for a U.S. steel manufacturer, Alessandria, Kaboski, and Midrigan (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_F to ensure that the interval between orders is on average 150 days in the low-uncertainty state.¹⁶ This implies $f_F = 0.00005846$ as our baseline value. Matching the interval of 85 days for domestic flows would imply $f_D = 0.00001057$. These fixed costs differ by a large amount (by a factor of about 5.5), and that difference might seem implausibly large. However, in the theory appendix we show that quantitatively we can still obtain large declines in trade flows in response to uncertainty shocks even with values for f_F that are not so high as in this baseline specification. That is, we are able to obtain a large decline in trade flows for a ratio of f_F/f_D that is lower than implied by the above values, and which might be considered more realistic.

standard deviation is proportional to the square root of λ . Thus, we have to quadruple λ_0 to double the standard deviation. This parameterization is also consistent with Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018, Table V). They roughly double the standard deviation in the high-uncertainty state at the aggregate level. They more than triple it based on an idiosyncratic shock process and micro-level data. But since there are no idiosyncratic shocks in our model, we prefer to side with the more conservative rise.

¹⁶In the model the interval between orders corresponds to the normalized bandwidth, $(S_0 - s_0)/\delta$. In the case of f_F we set it equal to 150 days, or 150/365 years. Hornok and Koren (2015) report that the average time for importing across 179 countries, excluding the actual shipping time, is around one month. Longer shipping times are associated with less frequent shipments. Also see Kropf and Sauré (2014) for estimates of substantial fixed shipment costs based on transaction-level data.

Figure 1: Change in s, S bounds (trigger point, return point) due to higher uncertainty. The low-uncertainty state is in grey, the high-uncertainty state is in black.

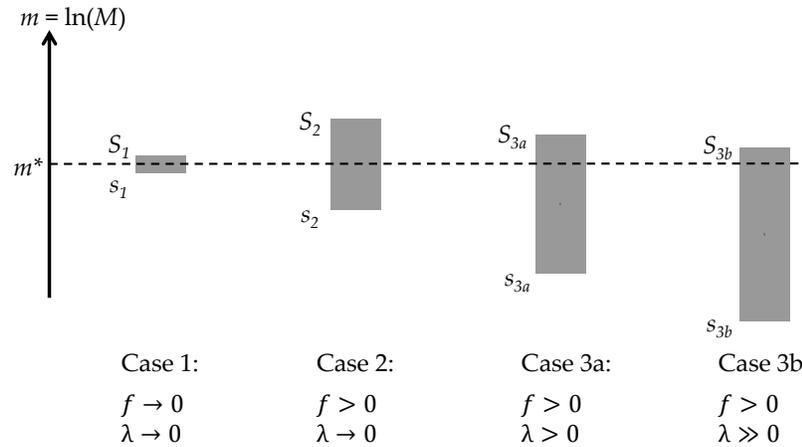


4.2. A Rise in Uncertainty

Given the above parameter values we solve the model numerically. Figure 1 illustrates the change in s, S bounds in response to rising uncertainty. The vertical scale indicates the percentage deviation from the target m^* . 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 $\lambda_0 = 1$ but the level of high uncertainty λ_1 varies on the horizontal axis (as our baseline value we will use $\lambda_1 = 4$ in later sections). At $\lambda_0 = \lambda_1 = 1$ the bounds for the two states coincide, by construction. As the s, S bounds are endogenous, all of them in principle shift in response to an increase λ_1 . But clearly, the bounds for the low-uncertainty state are essentially not affected by a rising λ_1 .

Two observations stand out. First, the lower trigger point always deviates further from the target than the return point. This is true for both states of uncertainty (i.e., $|s_0| > S_0$ and $|s_1| > S_1$). As we show in the theory appendix, in the presence of uncertainty a symmetric band around the target (i.e., $|s_\omega| = S_0$) would not be optimal. The reason is

Figure 2: Summary: How uncertainty pushes down the s, S bounds and increases the bandwidth.



that with uncertainty, there is a positive probability of the firm's output getting hit by a shock, leading the firm to adjust its inventory to the return point. Thus, the higher the shock probability, the more frequently the firm would adjust its inventory above target. To counteract this tendency it is optimal for the firm to set the return point relatively closer to the target.

Second, the bounds for the high-uncertainty state decrease with the extent of uncertainty, i.e., $\partial S_1 / \partial \lambda_1 < 0$ and $\partial s_1 / \partial \lambda_1 < 0$. The intuition for the drop in the return point S_1 is the same as above—increasing uncertainty means more frequent adjustment so that S_1 needs to be lowered to avoid excessive inventory holdings. The intuition for the drop in the lower trigger point s_1 reflects the rising option value of waiting. Suppose the firm is facing a low level of inventory and decides to pay the fixed costs of ordering f to stock up. If the firm gets hit by a shock in the next instant, it would have to pay f again. The firm could have saved one round of fixed costs by waiting. Waiting longer corresponds to a lower value of s_1 . This logic follows immediately from the literature on uncertainty and the option value of waiting (McDonald and Siegel 1986; Dixit 1989; Pindyck 1991).

Figure 2 summarizes the main qualitative results in a compact way. Case 1 depicts the (hypothetical) situation where both fixed costs f and uncertainty λ are negligible. Due to

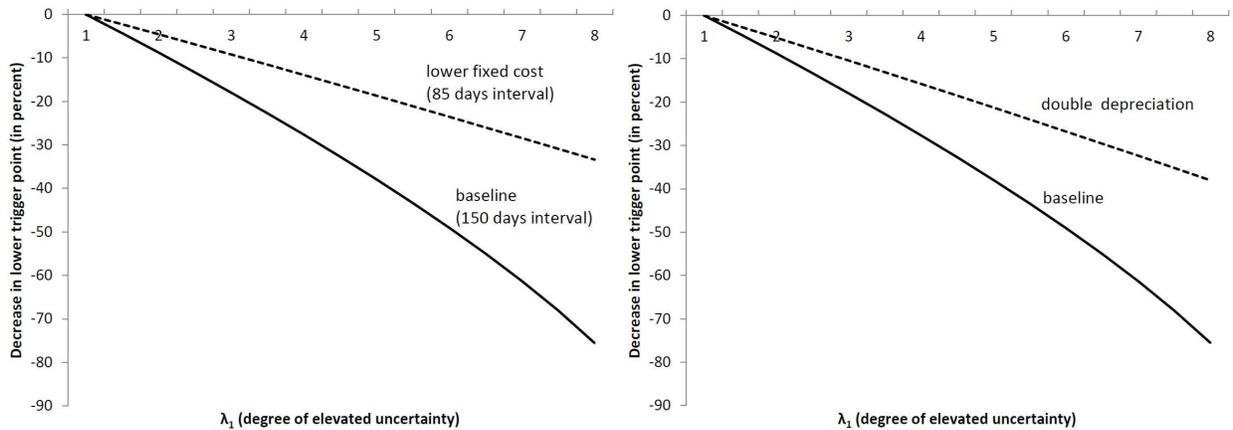
the very low fixed costs the bandwidth (i.e., the height of the box) is tiny, and due to the lack of uncertainty the s_1 and S_1 bounds are essentially symmetric around the target level m^* . In case 2 the fixed costs become larger, which pushes both s_1 and S_1 further away from the target but in a symmetric way. Cases 3a and 3b correspond to the situation we consider in this paper with non-negligible degrees of uncertainty. The uncertainty in case 3a induces two effects compared to case 2. First, both s_1 and S_1 shift down so that they are no longer symmetric around the target. Second, the bandwidth increases further. A shift to even more uncertainty (case 3b) reinforces these two effects.

4.3. Comparative Statics

We have assumed fixed costs of ordering to be lower when the input is ordered domestically, i.e., $f_D < f_F$. The left panel of Figure 3 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 that corresponds to 150 days. Lower fixed costs imply more frequent ordering and therefore allow the firm to keep its inventory closer to the target level. This means that for any given level of uncertainty, the optimal lower trigger point with low fixed costs does not deviate as far from the target compared to the high fixed cost scenario.

Some types of imports observed in the data are inherently difficult to store as inventory—for instance, nondurable goods. We model such a difference in storability with a higher rate of depreciation of $\delta = 0.2$ compared to the baseline value of $\delta = 0.1$. In general, the larger the depreciation rate, the smaller the decreases in the lower trigger point and the return point in response to heightened uncertainty. Intuitively, with a larger depreciation rate the firm orders more frequently. The value of waiting is therefore diminished. The right panel of Figure 3 graphs the percentage decline in the lower trigger point s_1 relative to s_0 for both the baseline depreciation rate and the higher value. We provide more comparative statics results for changes in f and δ in the theory appendix.

Figure 3: *The effect of a lower fixed costs (left) and a higher depreciation rate (right) of ordering on the decrease in the lower trigger point.*



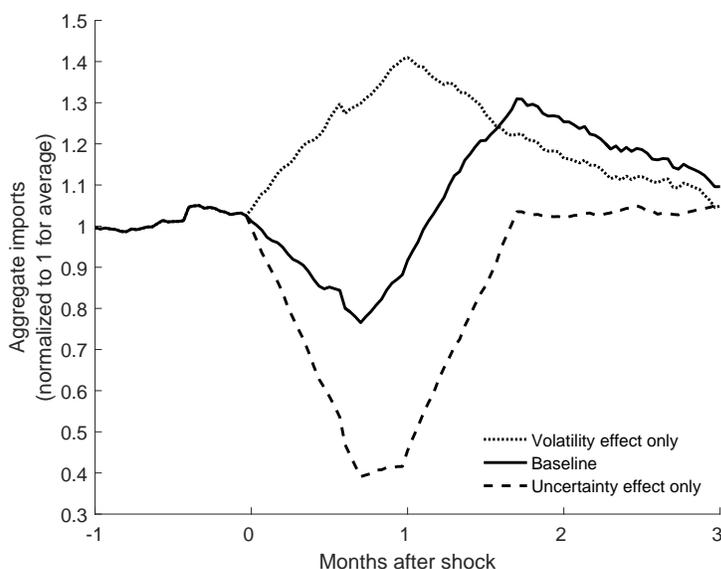
5. SIMULATING UNCERTAINTY SHOCKS

So far we have described the behavior of a single firm. We now simulate an economy of 50,000 firms in partial equilibrium where each individual firm receives shocks according to the stochastic uncertainty process in equations (5) and (6). These shocks are idiosyncratic for each firm but drawn from the same distribution. The firms are identical in all other respects. We use the same parameter values as in section 4.1, and we focus on the foreign-sourced input K_F and the associated fixed costs f_F .

We simulate an uncertainty shock by permanently shifting the economy from low uncertainty λ_0 to high uncertainty λ_1 . A key result from section 4.2 is that firms lower their s, S bounds in response to increased uncertainty. This shift leads to a strong downward adjustment of input inventories and thus a strong decline in imports.

In Figure 4 we plot simulated imports, normalized to 1 for the average value, in continuous time (focus on the solid line; we will explain the dashed and dotted lines below). Given our parameterization imports decrease by up to 25% at an instant in response to the shock. The decrease happens quickly within one month, followed by

Figure 4: *Simulating and decomposing the response of aggregate imports to an uncertainty shock: The total effect (baseline), the ‘pure’ uncertainty effect and the volatility effect.*



a quick recovery and in fact an overshoot (we comment on the overshoot below). This pattern of sharp contraction and recovery is typical for uncertainty shocks. In the theory appendix, as a comparison we express the same simulated data in discrete time at monthly frequency. There, we also allow for a temporary shock where uncertainty shifts back to its low level.

In our model the reaction of aggregate imports can be more clearly thought of in terms of two effects, depicted in Figure 4. The dashed line (at the bottom) represents a ‘pure’ *uncertainty effect*, and the dotted line (at the top) is a *volatility effect*. The volatility effect is responsible for the overshoot, and we comment on it in more detail in the theory appendix.

While the trade collapse and recovery happen quickly in the simulation, this process takes longer in the data. For instance, during the Great Recession German imports peaked in the second quarter of 2008, rapidly declined by 32% and only returned to their previous level by the third quarter of 2011.¹⁷ Greater persistence could be

¹⁷Most high-income countries experienced similar patterns. U.S. and Japanese imports

introduced into our simulation by staggering firms' responses. Currently, all firms perceive uncertainty in exactly the same way and thus synchronize their reactions. It might be more realistic to introduce some degree of heterogeneity by allowing firms to react at slightly different times. In particular, firms might have different assessments as to the time when uncertainty has faded and business conditions have normalized (see Bernanke 1983). This would stretch out the recovery of trade, and it would also diminish the amplitude of the impact. Moreover, delivery lags could be introduced that vary across industries. We abstracted from such extensions here in order to keep the model tractable.

Apart from being heterogeneous in terms of when they react to a shock, firms could also differ in more fundamental ways. Consistent with the literature on heterogeneous firms and trade, aggregate imports tend to be dominated by the most productive firms in an economy. Only those firms are able to cover the higher fixed costs of sourcing inputs from abroad. In the current model, we do not model an extensive margin response, i.e., firms do not switch from a foreign to a domestic supplier over the simulation period, or vice versa.¹⁸ Allowing for extensive margin responses would be an important avenue for future research. We conjecture that the extensive margin would amplify uncertainty shocks. Firms would likely switch to domestic suppliers in the face of higher uncertainty, thus reinforcing the effects of higher uncertainty. But since changing suppliers

declined by 38% and 40% over that period, respectively (source: IMF, Direction of Trade Statistics).

¹⁸This approach is motivated by empirical evidence based on micro data. Examining Belgian firm-level data during the 2008–09 recession, Behrens, Corcos, and Mion (2013) find that most of the changes in international trade across trading partners and products occurred at the intensive margin, while trade fell most for consumer durables and capital goods. Bricongne et al. (2012) confirm the overarching importance of the intensive margin for French firm-level export data. Haddad, Harrison, and Hausman (2010) present similar evidence for U.S. imports, which we consider in our empirical analysis.

entails switching costs, an extensive margin response might also make the effect of an uncertainty shock more persistent in the aggregate. Firms will not switch to domestic suppliers immediately but rather wait a while such that the overall effect on international trade flows is more drawn out. Moreover, once the uncertainty shock has subsided, firms might be slow in switching back to foreign suppliers, delaying the recovery. Of course, to trace this mechanism we would need firm-level data on foreign and domestic input orders, both at a reasonably high frequency. Alternatively, and trivially, persistence might arise by having multiple persistent uncertainty shocks arrive one after the other. This may well match the reality of 2008 and is an approach we explore later in section 7.

In the theory appendix we provide further simulation results involving comparative statics (changes in fixed costs and the depreciation rate). We also explore the role of first-moment shocks.

6. EMPIRICAL EVIDENCE

We now turn to the task of providing more formal empirical evidence for the new theoretical channels linking uncertainty shocks to domestic activity and foreign trade that we have proposed. Specifically, we set out to explore the dynamic relationship between uncertainty, production and international trade by estimating vector autoregressions (VARs) with U.S. data. Here, for comparability, we deliberately follow current state of the art, and we follow the canonical framework established by 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, the payoffs to an uncertainty-based approach can be substantial in the new setting we propose for modeling trade volatility. Why? 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.

The same might then be said of theories of the trade collapse that rely on negative productivity shocks.¹⁹ So 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.

The model above, and evidence below, can thus be seamlessly integrated with the closed-economy view of uncertainty-driven recessions, whilst matching a separate and distinct aggregate phenomenon that has long vexed international economists. Our new approach tackles an enduring puzzle, a 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. Testable Hypotheses

To sum up the bottom line, our empirical results expose new and important stylized facts that are consistent with our theoretical framework.

First, trade volumes do respond to uncertainty shocks, and the impacts are quantitatively and statistically significant. In addition, trade volume responds much more to uncertainty shocks than does the volume of industrial production; this magnification shows that there is something fundamentally different about the dynamics of traded

¹⁹Of course, first-moment demand shocks are less controversial in the context of the Great Trade Collapse.

goods supplied via the import channel, as compared to supply originating from domestic industrial production.

Second, we will 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. In addition, we find that the impact and magnification are 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 a decrease in perishability) leads to a larger response.

The subsequent parts of this section are structured as follows. The first part briefly spells out the empirical VAR methods we employ. 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 parts discuss our findings.

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. In his setup, this shock amounts to an increase in the variance, but not the mean, of a composite ‘business conditions’ 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., changes in the VXO U.S. stock-market volatility index are used as a proxy for the uncertainty shock. The VXO, and its newer cousin VIX, provided by the Chicago Board Options Exchange, have formed the basis of the most-widely traded options-implied

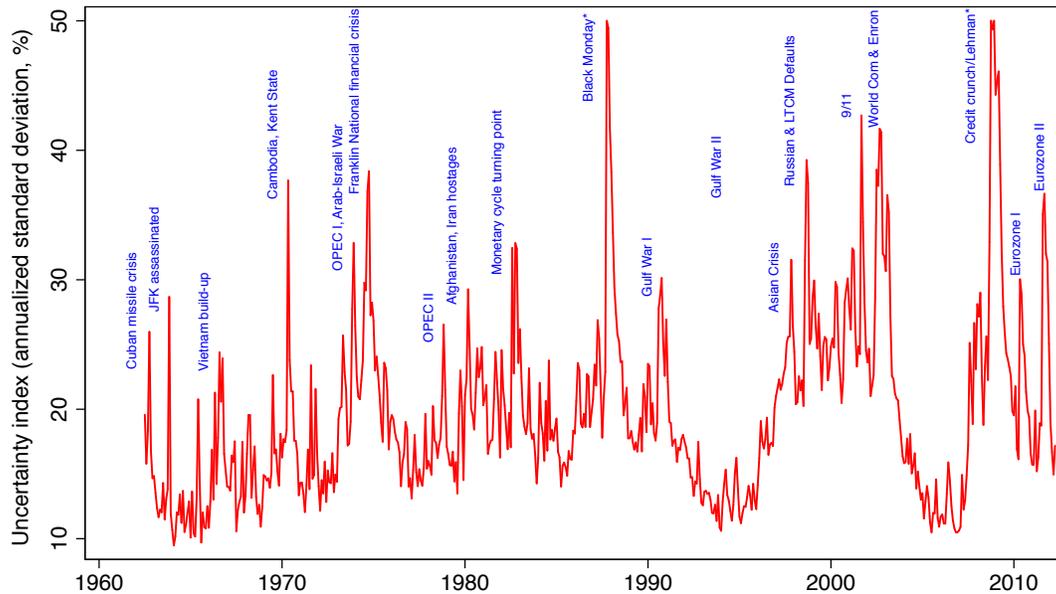
volatility contracts and they reference the daily standard deviation of the S&P 500 index over a 30-day forward horizon. With an implicit nod to rational expectations, realized volatility was used to backfill a proxy for VXO in historical periods before 1986 back to 1962 when the VXO is not available. A plot of this series, scaled to an annualized form, and extended to 2012 for use here, is shown in Figure 5.²⁰

We evaluate the impact of uncertainty shocks using VARs on monthly data from 1962 (the same as in Bloom) to February 2012 (going beyond Bloom's end date of June 2008). The full set of variables, in VAR estimation Cholesky ordering 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). We do not find our results are sensitive to the Cholesky ordering.²¹ For simplicity, the baseline results we present are estimated using a more basic quadvariate

²⁰As 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. 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.

²¹We follow Bloom (2009) exactly for comparability. As he 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."

Figure 5: *The uncertainty index: Monthly U.S. stock market volatility, 1962–2012.*



Notes: VIX index, and proxies. Capped at 50 (*). From Bloom (2009) and updates. See appendix.

VAR (log stock-market levels, the volatility indicator, log employment, and lastly the industrial production or trade indicator).

6.3. Data

Many of our key variables are exactly as in Bloom (2009): log industrial production in manufacturing (Federal Reserve Board of Governors, seasonally adjusted), employment in manufacturing (BLS, seasonally adjusted), a monthly stock-market volatility indicator as above, and the log of the S&P500 stock-market index. All variables are HP detrended, with parameter $\lambda = 129,600$. Full details are provided in the data appendix. Collection of these data was updated to February 2012.

However, in some key respects, our data requirements are much larger. 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, 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.

We briefly explain the provenance of these newly collected data, all of which are also HP filtered for use in the VARs, as above. More details of sources and construction are given in the data appendix.

- U.S. aggregated monthly real import volume. These data run from 1962:1 to 2012:2. After 1989, total imports for general consumption were obtained from the USITC dataweb. From 1968 to 1988 data were collected by hand from FT900 reports, where imports are only available from 1968 as F.A.S. (free alongside ship) at foreign port of export, general imports, seasonally unadjusted; the series change to C.I.F. (cost, insurance, and freight) 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 1989:1 to 2012:2. In each month total imports for general consumption disaggregated at the 4-digit NAICS level were obtained from the USITC dataweb. 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 1972:1 to 2012:2 at a useful level of granularity. Although aggregate IP data are provided by the Fed going back to 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 permits sector-by-sector compatibility with the import data above. From 1972 we used Fed G.17 reports to compile sector-level IP indices, yielding data on 98 sectors at the start, expanding to 99 in 1986.

6.4. IRFs at Aggregate Level for Trade and IP

The world witnessed an unusually steep decline in international trade in 2008–09, the most dramatic since the Great Depression. International trade plummeted by 30% or more in many cases. Some countries suffered particularly badly. For example, Japanese imports declined by about 40% 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.” This synchronization hints at a common cause (Imbs 2010).

The first evidence we present on the importance of uncertainty shocks for trade uses aggregate data on U.S. real imports and industrial production (IP). We estimate a vector autoregression (VAR) with monthly data from 1962 through 2012, following the main specification in Bloom (2009) exactly, as explained above and more fully in the appendix.

Figure 6 presents our baseline quadvariate VAR results for the aggregate U.S. data, for both log real imports and log IP, as well as their ratio, all in a row. The impulse response functions (IRFs) from the VAR are based on a one-period uncertainty shock where the uncertainty measure increases by one unit (the measure is an equity market option implied-volatility index, VXO, all data are HP filtered, and more details will follow later in the main empirical part of the paper). In Figure 6a, the upper panel, we employ Bloom’s standard uncertainty shock series. In Figure 6b, the lower panel, to support the idea of causality, we rely on his ‘exogenous’ uncertainty shock series that only uses events

associated with terrorist attacks, war and oil shocks.

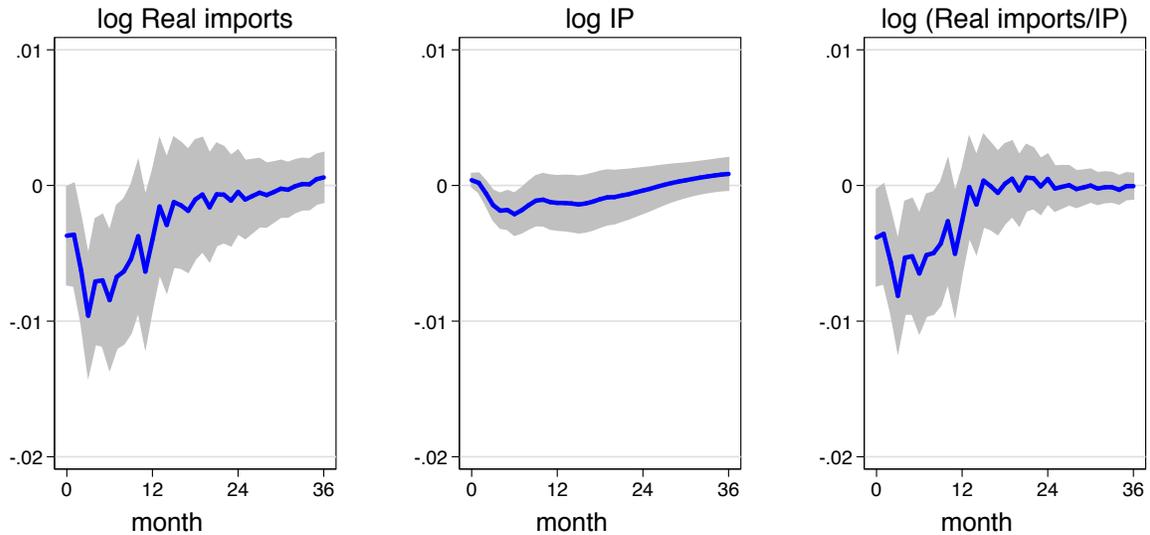
The bottom line is very clear from this figure. Look first at Figure 6a. The uncertainty shock is associated with a decline in both industrial production and imports. However, the response of imports is clearly many times stronger, about 5 to 10 times as strong on average in the period of peak impact 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. To confirm that the response of imports is more negative than the response of IP, the third chart in row 1 shows the IRF computed when using the log ratio of real imports to IP: clearly this ratio falls after an uncertainty shock, and the 95% confidence interval lies below zero.

To provide further evidence and a robustness check, Figure 6b, where now only the exogenous ‘clean’ uncertainty shocks indicator from Bloom (2009) is used, scaled by observed volatility, to purge endogenous uncertainty dynamics from the estimations.²² As this figure shows, even if we restrict attention to these events, which arguably provide a stricter approach to identification at the cost a smaller sample of candidate shocks, we get the same basic finding: a sharp negative shock to trade after an uncertainty shock, and a response that is much larger than that seen for industrial production. We also refer to the appendix where we provide additional IRF results based on the uncertainty measures by Baker, Bloom and Davis (2016) and Berger, Dew-Becker and Giglio (2019).

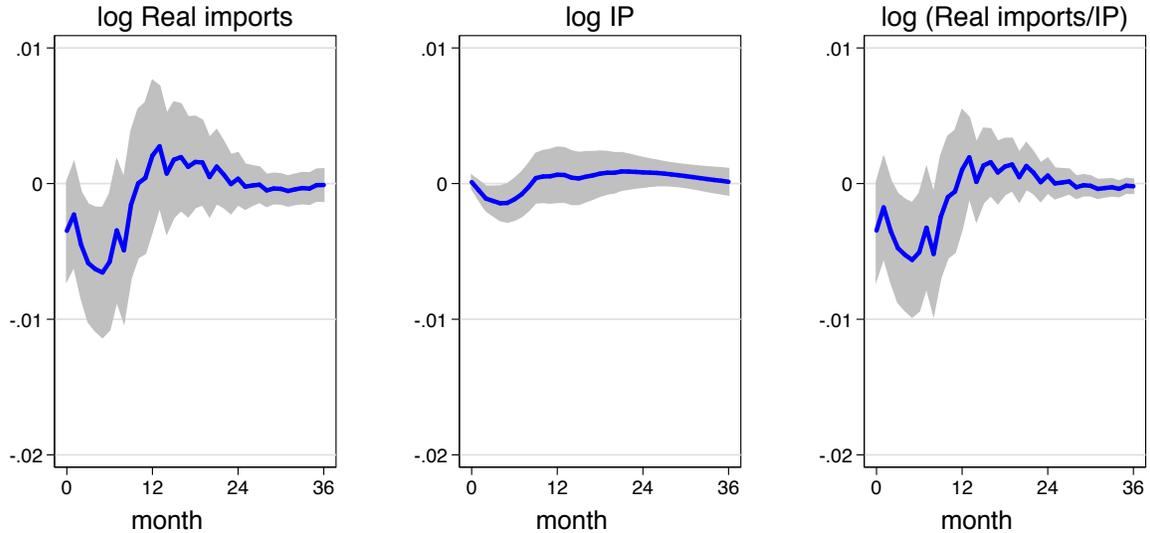
²²Virtually identical results, available upon request, are produced when the unscaled shock is used. Specifically, Bloom (2009) identifies 17 high-volatility episodes since the 1960s such as the assassination of JFK, the 1970s oil shocks, the Black Monday market crash of October 1987, the 1998 bailout of Long-Term Capital Management, 9/11, and the collapse of Lehman Brothers in September 2008. These high-volatility episodes are strongly correlated with alternative indicators of uncertainty.

Figure 6: IRFs at aggregate level for uncertainty shocks, proxied by VXO shocks.

(a) Basic VAR: Response to actual VXO uncertainty shocks.



(b) Exogenous shock VAR: Response to Bloom's 'exogenous' VXO-scaled shocks.



Notes: Sample is 1962:1–2012:2. The quadriariate VAR Cholesky ordering as in Bloom (2009) is: stock market, the volatility measure, log employment, followed lastly by either log real imports or log IP. In the first panel the volatility measure we use is actual VXO shocks, in the second panel we use Bloom's 'exogenous' VXO-scaled shocks. No rescaling of shocks. 95% confidence intervals shown. See text and appendix.

6.5. IRFs Disaggregated by Durables and Nondurables for Trade and IP

Having established empirically that trade reacts more negatively than IP to an uncertainty shock, we next look at the same responses at a disaggregated level. Specifically, we look at a key prediction of our model that these differences should be magnified in the case of more durable goods, as captured in the theoretical model by the depreciation parameter.

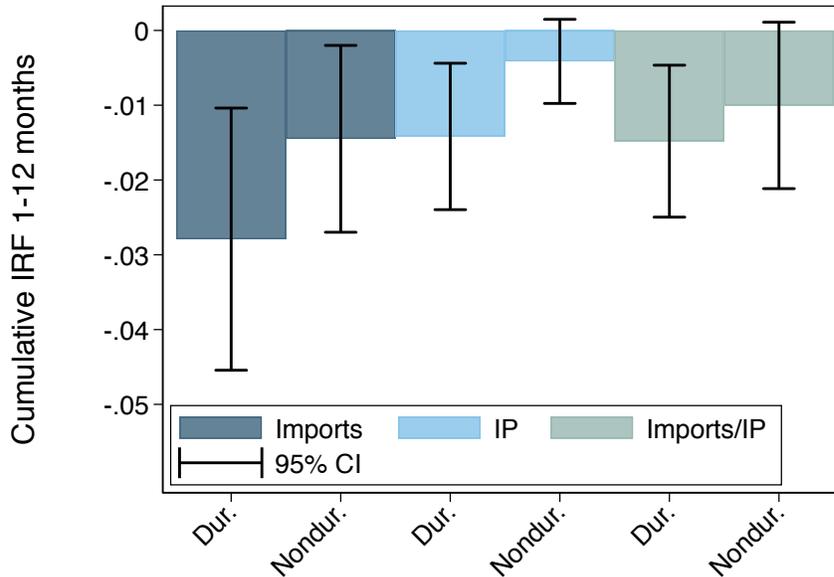
For this we move to the 3- or 4-digit NAICS level, sourcing data from USITC dataweb and the Fed G.17 releases at a monthly frequency starting in 1989. The overlap between these two sources allows us to work with 51 individual sectors. A list of NAICS codes at this level of disaggregation, with accompanying descriptors, is provided in the appendix. We re-estimate every IRF at this disaggregated level, using the exact same specification as before and repeating the exercise for each NAICS sector with imports and IP.

To offer a presentation of the results in a way that corresponds to the durable-nondurable distinction, we then aggregate up the IRFs into two bins, corresponding to durable and nondurable manufacturing sectors, according the NAICS classification of sectors by the BLS.²³ The resulting weighted average IRFs for months 1–12 are presented as summary statistics in Figure 7. The correspondence between the theoretical model's predictions and the estimated cumulative responses over the one-year horizon is notable. In nondurable goods sectors, the response to uncertainty shocks is small. In durable goods sectors, the response to uncertainty shocks is larger (2 times). In both cases the responses in real imports are larger than in IP (2 times), and that is confirmed when we look at the response of the ratio of real imports to IP: the durable response is large and statistically significant; the nondurable response is neither. Thus, on a key dimension, the disaggregated responses for durable and nondurable manufacturing sectors also accord with the theoretical mechanism we propose.²⁴ However, since the confidence intervals of

²³See <https://www.bls.gov/jlt/jltnaics.htm>.

²⁴In the appendix we offer further results by classifying industries according to End Use categories.

Figure 7: Average real import and IP IRFs compared in months 1–12 for manufacturing industries, by BLS durable-nondurable bins, with underlying IRF estimation at the 3- or 4-digit NAICS level.



Notes: Cumulative IRF for months 1–12. Flow data at the 3- or 4-digit NAICS level, aggregated up to BLS durable-nondurable bins for manufacturing industries using output weights from the Fed’s U.S. 2002 makeuse table. 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 quadivariate VARs. 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. See text and appendix.

the IRFs largely overlap for the durable-nondurable bins, our preferred interpretation is to emphasize the qualitative result of a significant response for durables. We urge more caution about the precise point estimates.

Finally, we refer to the appendix where we provide additional robustness checks exploiting the granting of Permanent Normal Trade Relations (PNTR) status to China (see Pierce and Schott 2016; Handley and Limão 2017). There we employ U.S. import data

from China and the European Union at the four-digit level.

6.6. IRFs Disaggregated by Source Country Fixed Costs

Next, we look at another key prediction of our model: that differences in responses to uncertainty shocks should be magnified when fixed costs of importing are higher, as captured in the theoretical model by the f_F parameter.

To test this we divide monthly U.S. imports into two bins, for source countries that are in the lowest and highest quartiles of the World Bank's "Ease of Doing Business" (EODB) index.²⁵ We think this is a reasonable proxy for variations in country-specific fixed (rather than variable) costs of doing business which would affect firms trying to export from that source to the U.S.

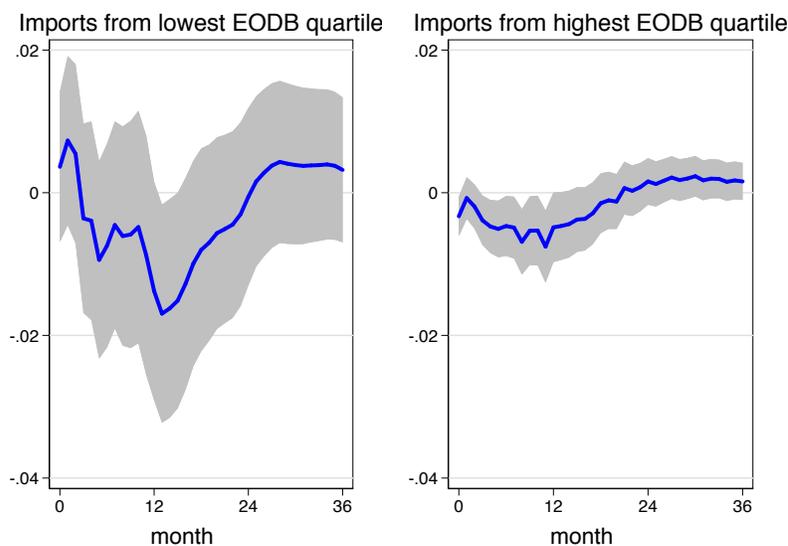
Figure 8 contains the results of this exercise, conducted on the sample period 1989:1–2012:12. The left panel shows that U.S. imports from countries with high fixed costs (low EODB) have large amplitude responses to our measure of uncertainty shocks, but the right panel shows that countries with low fixed costs (high EODB) have relatively small amplitude responses in comparison. Thus, our results seem consistent with the model's prediction although quantitatively, the confidence intervals in the two panels overlap.

7. CAN THE GREAT TRADE COLLAPSE OF 2008–09 BE EXPLAINED?

We have shown that empirical evidence over recent decades suggests a tight link between uncertainty shocks and trade contractions, especially for durable goods, in a way that is *qualitatively* consistent with our theoretical framework. Now we wrap up by asking a rather more demanding question: to what extent can this approach, which takes second-moment uncertainty shocks seriously as a main driver, provide a *quantitatively* plausible account of the Great Trade Collapse of 2008–09?

²⁵See <http://www.doingbusiness.org/rankings>.

Figure 8: IRFs at aggregate level for high- and low-fixed cost source countries (low and high EODB, respectively).

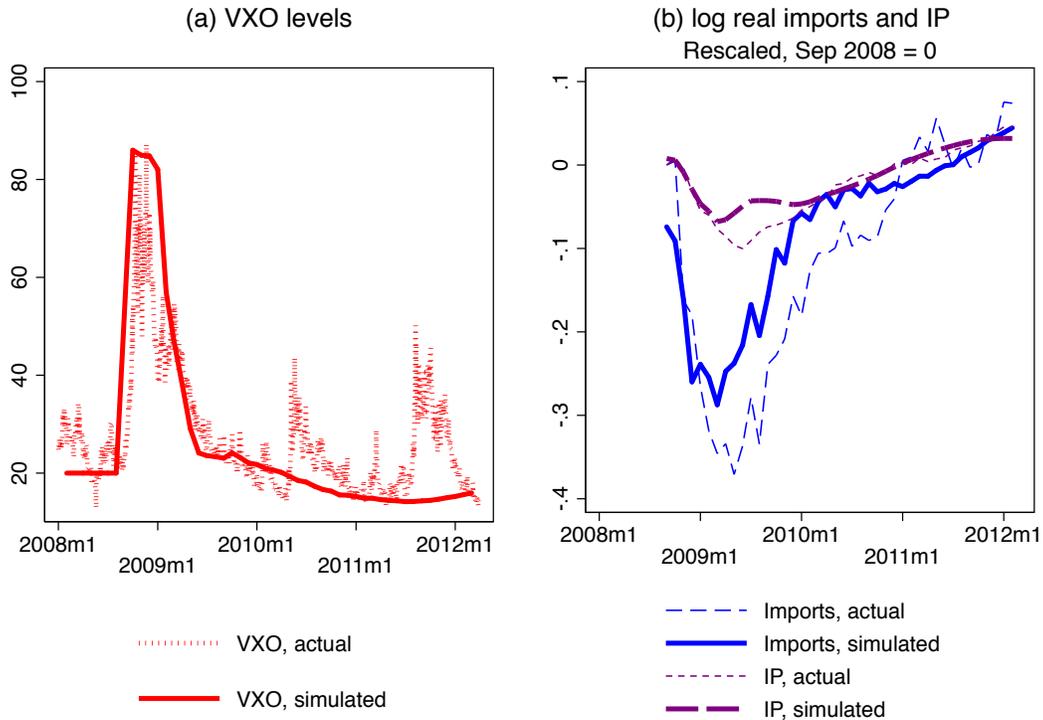


Notes: Sample is 1989:1–2012:12. The quadri-variate VAR Cholesky ordering as in Bloom (2009) is: stock market, the volatility measure, log employment, followed lastly by either log real imports or log IP. As the volatility measure we use is actual VXO shocks. No rescaling of shocks. 95% confidence intervals shown. See text and appendix.

We thus conclude by presenting a simulation exercise, using our baseline aggregate VAR from section 6, to argue that this mechanism could indeed have been an important contributing factor, even if other forces were in play. To do this we need to construct a set of plausible exogenous shocks to the uncertainty variable that match its observed outcomes in the crisis, and then feed them into the VAR model to obtain predicted paths for imports and IP which can be compared to actual post-2008 outcomes.

As is well known, the four months following the collapse of Lehman Brothers were characterized by strong increases in uncertainty as measured by the volatility index VXO in the period September to December 2008, with elevated volatility persisting into the first quarter of 2009. To simulate this shock we choose to feed into the model a series of exogenous volatility shocks which generate a path of volatility similar to that observed.

Figure 9: Actual and simulated VXO, real imports and IP during and after the the 2008 “Lehman” uncertainty shock.



That is, we assume that the dynamics are driven primarily by an exogenous shock to the system from the volatility index and the subsequent endogenous responses of the variables in the system.

We found in the baseline VAR that the own-response of volatility to itself in the orthogonalized impulse response (not shown here) is about 3, with significant short-term persistence. In mid-2008 the real-world data showed a VXO level of 20, which we take as a starting value for our simulation, and which in the VAR we then subject to a series monthly shocks of +20,+5,+5,+5,+5,+5,+5 starting in September 2008. Through endogenous VAR dynamics, these shocks take simulated VXO up to just over 80 at peak (via cumulation/persistence), and the additional shocks keep the simulated VXO very elevated for several months before the decay commences. In actuality, the real-world

VXO rose from its pre-crisis mean of about 20 to almost 90 in the last quarter of 2008, a shift of +70, and thus the simulated impulses we impose create a close match to the actual path of VXO quite well, as shown in Figure 9, in the left panel. Could such shocks generate a large trade collapse with a magnification effect present?

Yes, to some extent. Given these “Lehman shocks” imposed to the VXO process starting from its starting level of 20, the model-implied and the actual observed responses of IP and real imports are shown in Figure 9, in the right panel, relative to a September 2008 reference level. As can be seen, the model is capable of explaining a large fraction of the actual observed IP response, especially up to 6 months out. It is also capable of explaining a decent fraction of the real import response over a similar horizon. Overall, these simulations show that, if we push hard on these very specific shocks, our model can explain perhaps around half of the import collapse out to the 12-month horizon.

All that said, we want to be cautious and not claim too much: we can see that, especially in early to mid-2009, some additional factors must have been at work that are not captured by the uncertainty shock. This suggests our approach should be viewed as a partial attempt and complementary to other explanations put forward in the literature on the Great Trade Collapse such as trade credit shocks, especially in the acute phase of the crisis (see section 2).

In their survey of that literature, Bems, Johnson, and Yi (2013) note that no study has so far integrated the various competing explanations into a unified framework. Nevertheless, based on estimates from various independent papers but excluding the role of second-moment shocks, they loosely suggest that 65-80 percent of the trade collapse could be attributed to compositional effects associated with changes in final expenditure and trade-intensive durable goods in particular. A further 15-20 percent are due to credit supply shocks. Inventory adjustments as an amplification mechanism may account for around 20 percent.²⁶ Our work suggests that the latter share may be larger because of

²⁶These estimates do not necessarily sum up to 100 percent since they are obtained from

second-moment shocks, not least since inventories are relevant both for intermediate and final goods. But a precise decomposition is yet to be carried out and remains as an important topic for future work. Last but not least, we believe that uncertainty shocks may also provide a better handle on the recovery dynamics as shown in Figure 9, capturing both the decline and the resurgence of trade.

8. CONCLUSION

We argue that trade can be modeled as reacting to uncertainty shocks in theory and in practice. We introduce second-moment uncertainty shocks into a dynamic, open-economy model. Firms import inputs and due to fixed costs of ordering follow an optimal s, S inventory policy. We show that elevated uncertainty leads firms to shift down their s, S bounds. This induces a sharp contraction of international trade flows followed by a swift recovery. In contrast, output remains unaffected, assuming other shocks are absent. Uncertainty shocks can therefore explain why trade is more volatile than domestic economic activity.

Qualitatively, our empirical evidence suggests a tight link between uncertainty shocks and trade contractions, and we can also show that there is substantial heterogeneity in responses at the sectoral level, both for imports and industrial production, in a way consistent with our proposed model.

Quantitatively, our simulation results offer a partial explanation for the Great Trade Collapse of 2008–09, and potentially for previous trade slowdowns, in a way that differs from the conventional static trade models or dynamic inventory models seen before. The introduction of second-moment shocks may be useful as a driver since the required first-moment shocks are either absent on the impulse side or insufficient on the propagation side (for plausible parameters) to fully explain the events witnessed.

independent papers.

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Online Appendix to “Trade and Uncertainty”

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Appendix A.1: Solving the Inventory Problem This appendix shows how the inventory problem can be solved. We closely follow Hassler (1996) and refer to his appendix for further details.

The Bellman equation for the inventory problem is

$$V(z_t, \omega_t) = \frac{1}{2}z_t^2 dt + (1 - rdt)E_t V(z_{t+dt}, \omega_{t+dt}). \quad (\text{A1})$$

The cost function $V(z_t, \omega_t)$ at time t in state ω_t thus depends on the instantaneous loss element from the minimand (4), $z_t^2 dt/2$, as well as the discounted expected cost at time $t + dt$. The second term can be further broken down as follows:

$$\begin{aligned} E_t V(z_{t+dt}, \omega_{t+dt}) = & V_z(z_t, \omega_t) - \delta dt V_z(z_t, \omega_t) \\ & + \lambda_\omega dt \{V(S_\omega, \omega_t) + f - V(z_t, \omega_t)\} \\ & + \gamma_\omega dt \{V(z_t, \bar{\omega}_t) - V(z_t, \omega_t)\}, \end{aligned} \quad (\text{A2})$$

where V_z denotes the derivative of V with respect to z . The expected cost at time $t + dt$ thus takes into account the cost of depreciation over time through the term involving δ . It also captures the probability $\lambda_\omega dt$ of a shock hitting the firm's business conditions (in which case the firm would pay the ordering costs f to return to point S_ω), as well as the probability $\gamma_\omega dt$ that the uncertainty state switches from ω_t to $\bar{\omega}_t$.

Equations (A1) and (A2) form a system of two differential equations for the two possible states ω_t and $\bar{\omega}_t$. Standard stochastic calculus techniques lead to a solution for the system. We have to use numerical methods to obtain values for the four main endogenous variables of interest: the bounds s_0 and S_0 for the state of low uncertainty λ_0 , and the bounds s_1 and S_1 for the state of high uncertainty λ_1 . It turns out that in either state ω , the cost function V reaches its lowest level at the respective return point S_ω . This point represents the level of inventory the firm ideally wants to hold given the expected outlook for business conditions and given it has just paid the fixed costs f for adjusting its inventory. It is not optimal for a firm to return to a point at which the cost function is above its minimum. The intuition is that if it were so, the firm on average

would spend less time in the lowest range of possible cost values.

We plug the expression for $E_t V(z_{t+dt}, \omega_{t+dt})$ from equation (A2) into equation (A1). We then set $dt^2 = 0$ and divide by dt to arrive at the following system of differential equations:

$$rV(z_t, \omega_t) = \frac{1}{2}z_t^2 - \delta V_z(z_t, \omega_t) + \lambda_\omega \{V(S_\omega, \omega_t) + f - V(z_t, \omega_t)\} + \gamma_\omega \{V(z_t, \bar{\omega}_t) - V(z_t, \omega_t)\}.$$

The set of solutions to this system is given by

$$V(z_t, 0) = \frac{\alpha_0}{2}z_t^2 + \beta_0 z_t + c_1 e^{\rho_1 z_t} + c_2 e^{\rho_2 z_t} + \phi_0 + \frac{1}{\Delta} \{\lambda_1 \gamma_0 V(S_1, 1) + \lambda_0 \psi_1 V(S_0, 0)\} \quad (\text{A3})$$

for the state of low uncertainty, and

$$V(z_t, 1) = \frac{\alpha_1}{2}z_t^2 + \beta_1 z_t + v_1 c_1 e^{\rho_1 z_t} + v_2 c_2 e^{\rho_2 z_t} + \phi_1 + \frac{1}{\Delta} \{\lambda_1 \psi_0 V(S_1, 1) + \lambda_0 \gamma_1 V(S_0, 0)\} \quad (\text{A4})$$

for the state of high uncertainty, where c_1 and c_2 are the integration constants. The parameters ψ_0 , ψ_1 , Δ , α_0 , α_1 , β_0 , β_1 , ϕ_0 and ϕ_1 are given by

$$\psi_\omega = r + \lambda_\omega + \gamma_\omega,$$

$$\Delta = \psi_0 \psi_1 - \gamma_0 \gamma_1,$$

$$\alpha_\omega = \frac{1}{\Delta} (r + \lambda_{\bar{\omega}} + \gamma_{\bar{\omega}} + \gamma_\omega),$$

$$\beta_\omega = -\frac{\delta}{\Delta} (\psi_{\bar{\omega}} \alpha_\omega + \gamma_\omega \alpha_{\bar{\omega}}),$$

$$\phi_\omega = \frac{1}{\Delta} (\psi_{\bar{\omega}} (\lambda_\omega f - \delta \beta_\omega) + \gamma_\omega (\lambda_{\bar{\omega}} f - \delta \beta_{\bar{\omega}})),$$

where $\bar{\omega} = 1$ if $\omega = 0$, and vice versa. $[v_i, 1]'$ is the eigenvector that corresponds to the eigenvalue ρ_i of the matrix

$$\frac{1}{\delta} \begin{bmatrix} -(r + \lambda_1 + \gamma_1) & \gamma_1 \\ \gamma_0 & -(r + \lambda_0 + \gamma_0) \end{bmatrix}$$

for $i = 1, 2$. Expressions for $V(S_0, 0)$ and $V(S_1, 1)$ can be obtained by setting $V(z_t, 0) = V(S_0, 0)$

and $V(z_t, 0) = V(S_1, 1)$ in equations (A3) and (A4), respectively, and then solving the two resulting equations.

Six key equations describe the solution. They are two value-matching conditions positing for each state of uncertainty that the value of the cost function at the return point must be equal to the value at the lower trigger point less the fixed ordering costs f :

$$V(S_0, 0) = V(s_0, 0) - f,$$

$$V(S_1, 1) = V(s_1, 1) - f.$$

The remaining four equations are smooth-pasting conditions:

$$V_z(S_0, 0) = 0,$$

$$V_z(s_0, 0) = 0,$$

$$V_z(S_1, 1) = 0,$$

$$V_z(s_1, 1) = 0.$$

These six conditions determine the six key parameters: the return points S_0 and S_1 , the lower trigger points s_0 and s_1 as well as the two integration constants c_1 and c_2 . Numerical methods have to be used to find them.

The following condition can be derived from the Bellman equation (A1):

$$\frac{1}{2} (s_\omega^2 - S_\omega^2) = (r + \lambda_\omega) f + \gamma_\omega \{f - (V(s_\omega, \bar{\omega}_t) - V(S_\omega, \bar{\omega}_t))\} > 0. \quad (\text{A5})$$

This expression can be shown to be strictly positive since each term is positive: $(r + \lambda_\omega) f > 0$ and, moreover, $\gamma_\omega \{f - (V(s_\omega, \bar{\omega}_t) - V(S_\omega, \bar{\omega}_t))\} \geq 0$. This last non-negativity result holds because the smallest value of V can always be reached by paying the fixed costs f and stocking up to S_ω . That is, for any z_t the cost value $V(z_t, \bar{\omega}_t)$ can never exceed the minimum value $V(S_\omega, \bar{\omega}_t)$ plus f . It therefore also follows that $V(s_\omega, \bar{\omega}_t)$ can never exceed $V(S_\omega, \bar{\omega}_t) + f$, i.e., $V(s_\omega, \bar{\omega}_t) \leq V(S_\omega, \bar{\omega}_t) + f$.

Recall that the lower trigger point s_ω is expressed as a deviation from the target level m^* . We therefore have $s_\omega < 0$. Conversely, the return point S_ω is always positive, $S_\omega > 0$. The fact that expression (A5) is positive implies $|s_\omega| > S_\omega$, i.e., the lower trigger point is further from the target than the return point. Why does this asymmetry arise? 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 below and above the target exactly half of the time, with the lower trigger point and return point equally distant from the target. However, in the presence of uncertainty this symmetry is no longer optimal. There is now a positive probability that output q gets hit by a shock according to equation (5). Whenever a shock hits, the firm adjusts its inventory to the return point S_ω . If the return point were the same distance from the target as the lower trigger point, the firm's inventory would on average be above target. To avoid this imbalance the firm chooses a return point that is relatively close to the target.

Appendix A.2: More Simulation Results We present more results on the simulation of an uncertainty shock as in section 5.

We first comment on decomposing the short-run dynamics. As depicted in Figure 4, the reaction of aggregate imports can be thought of in terms of two effects, an uncertainty effect and a volatility effect. The volatility effect is responsible for the overshoot.

The decomposition is computed as follows. The uncertainty effect only captures the shifting down of the s, S bounds (i.e., we use the lower bounds whilst holding the degree of volatility fixed at 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 drop in orders of imported inputs. Once firms approach the new lower trigger point, they start restocking. This leads to the recovery in orders.

The volatility effect is an opposing effect caused by the increased probability of firms receiving a shock (i.e., we switch to λ_1 from λ_0 whilst holding the s, S bounds fixed). This effect is analogous to the ‘volatility overshoot’ (see Bloom 2009, section 4.4). Recall that a shock ε moves output symmetrically in either direction with equal probability and always leads to adjustment. Suppose that all firms were exactly at the return point ($z = S$). Then the size of negative orders (induced by z being pushed above the upper trigger point) and the size of positive orders (induced by z being pushed below the lower trigger point) would be the same. Switching to λ_1 would increase the frequency of orders, but given that negative and positive orders would be of the same size and of equal probability, there would be no net effect on aggregate orders. However, most firms are in fact *below* the return point ($z < S$), which means that they have not stocked up in a while. Positive orders are therefore larger than negative orders, and increasing the frequency leads to a rise in aggregate orders temporarily.

Note that the total (baseline) effect surpasses the volatility effect in Figure 4 about one-and-a-half months into the period of heightened uncertainty. This happens due to the interaction of the volatility and uncertainty effects. While the volatility effect implies more frequent ordering and thus larger aggregate orders, it is reinforced by the increase in the bandwidth ($S - s$), which entails larger restocking orders all else being equal.

As Figure 4 shows, the drop in imports driven by the uncertainty effect is not instantaneous.

Instead, it is a smooth process. The reason is a combination of two countervailing effects. On the one hand, the lower trigger point s drops. This means that fewer firms adjust upon impact because they have more room to run down their inventories. On the other hand, the return point S also drops (see Figure 2). This means that firms adjust by less when they get hit by idiosyncratic ε shocks. These two effects balance each other evenly upon impact. But over time, as more and more firms run down their inventories further than previously, the first effect gradually starts to dominate, and average orders and imports begin to slide. In that context, below we graphically illustrate the inventory position of the average firm.

In the aggregate, imports eventually bounce back and even overshoot. The intuition for the overshoot is that aggregate output is flat because positive and negative shocks in equation (5) wash out. The initial drop in input orders therefore needs to be offset by a subsequent surge such that aggregate production can be held constant in the long run.

To simulate the model in discrete time, in the left panel of Figure A1 we express the same simulated data as in Figure 4 but at monthly frequency. The decrease is now around 15% in the first month after the shock. In the right panel of Figure A1 we allow for a temporary shock where uncertainty shifts back to its low level λ_0 after two months as opposed to staying permanently high at λ_1 . The removal of elevated uncertainty boosts the recovery but the initial decline remains. We stress that the short-run dynamics in Figures 4 and A1 are purely driven by second-moment shocks.

In Figure A2 we illustrate the inventory position of the average firm. Specifically, we plot the average deviation of imported inputs from the target level. In the steady state before the uncertainty shock hits, this deviation is close to zero. Upon impact, firms' average inventories start to decline as the uncertainty effect sinks in. At the same time, the higher volatility means that firms are more likely to restock, implying a rising average deviation over time. This volatility effect is initially dominated by the uncertainty effect, but firms' inventories eventually start rising after about a month into the period of heightened uncertainty.

We now turn to further simulations as in section 5. In the left panel of Figure A3 we plot the total effect of an uncertainty shock for two different values of fixed costs. The solid line is based on our baseline value for foreign fixed costs f_F that corresponds to an order interval of 150 days.

Figure A1: *Simulating aggregate imports in response to a permanent (left) and a temporary (right) shock, in discrete time.*

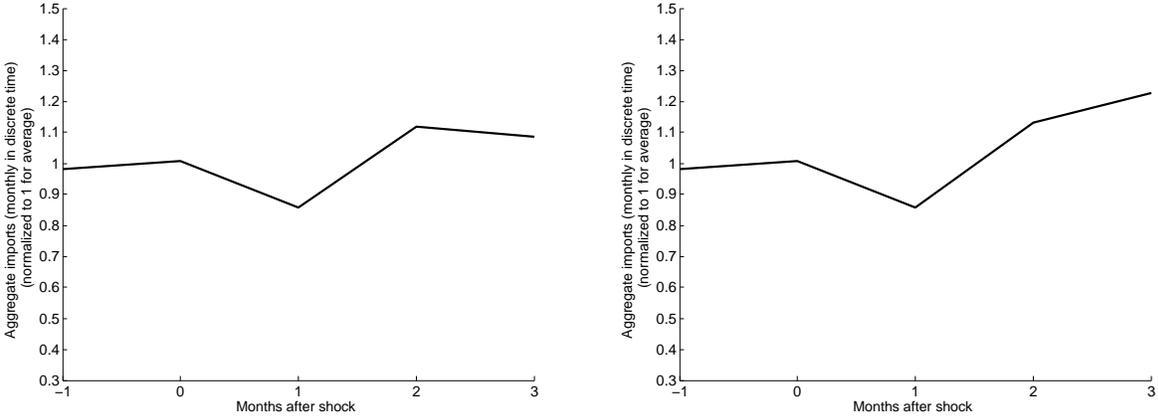


Figure A2: *Simulating the inventory position of the average firm.*

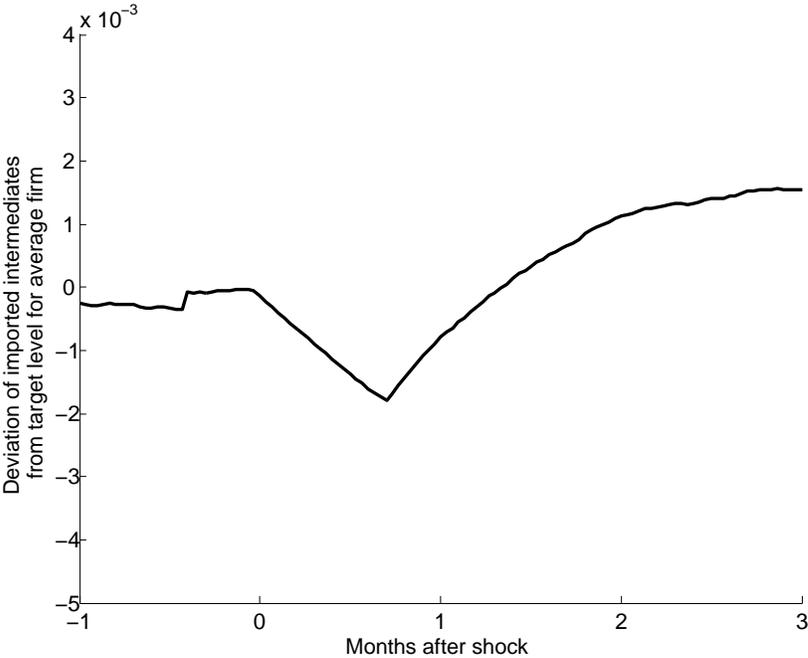
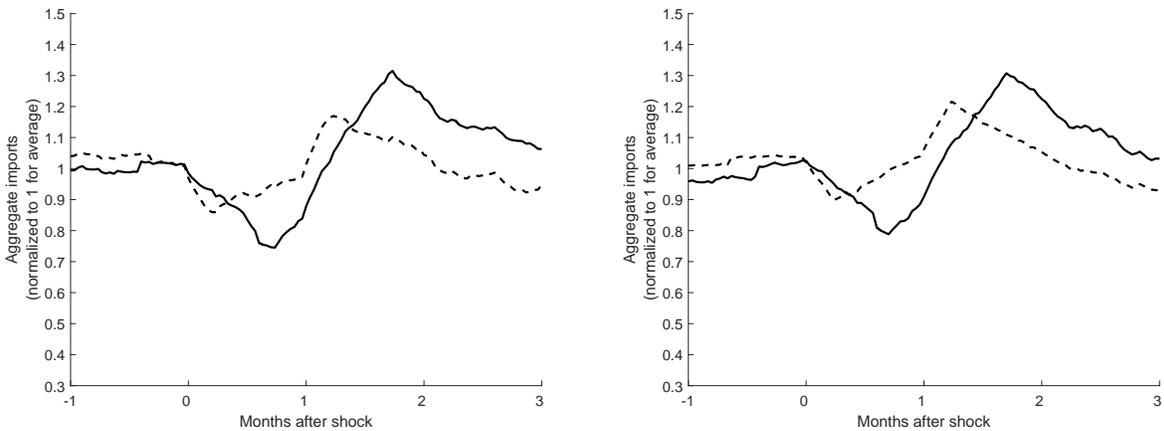


Figure A3: Simulating aggregate imports with different values of fixed costs of ordering (left) and different values of the depreciation rate (right).

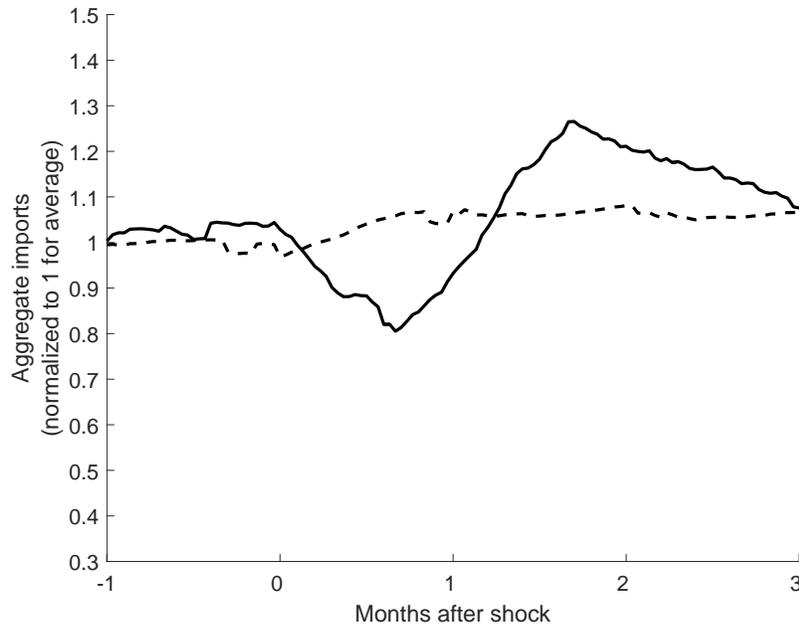


The dashed line represents domestic fixed costs f_D that correspond to an interval of 85 days. The ratio of foreign to domestic fixed costs, f_F/f_D , is 5.5 in this case (see the values in section 4.1).

As predicted by the theory, imports do not decline as much in the case of domestic orders. Their decline is roughly half in comparison to foreign orders. Moreover, they bottom out earlier. The reason is that the uncertainty effect from Figure 4 is weaker so that it gets offset more quickly by the volatility effect.

Another insight is that quantitatively, the trade collapse is not very sensitive to fixed costs above a certain threshold. For example, given an intermediate value of foreign fixed costs that corresponds to an order interval of 131 days corresponding to $f_F = 0.00003846$, imports still drop by over 20% (compared to 25% in the baseline scenario). The foreign to domestic fixed cost ratio is only 3.6 in this case instead of 5.5 above. In contrast, Alessandria, Kaboski, and Midrigan (2010a) use a ratio of $f_F/f_D = 6.5$, a much larger disparity in frictions. In their benchmark case (their Table 4), they choose values for fixed costs of ordering that correspond to 23.88 percent of mean revenues (a very large cost share) for foreign orders and 3.65 percent of mean revenues for domestic orders. The reason that smaller and arguably more plausible ratios suffice is as follows. The decline of the lower trigger point in response to an uncertainty shock (as depicted in Figure 3) is increasing but concave in f_F . Thus, increases in f_F have a strong marginal impact when f_F is low. Once f_F is high, increases have a weak impact on the lower trigger point. For instance, the impact on the lower trigger point associated with the baseline value of f_F makes up more

Figure A4: *Simulating aggregate imports with different values of the depreciation rate (10% for the solid line and an extreme value of 90% for the dashed line).*



than two-thirds (72%) of the impact associated with doubling f_F . (Given the parameterization in section 4.1, the baseline value of f_F is associated with a decline in the lower trigger point by 27.7% in response to an uncertainty shock. Doubling the baseline value of f_F is associated with a 38.4% decline. It follows $27.7/38.4 = 0.72$.)

In the right panel of Figure A3 we plot the effect of an uncertainty shock for two different values of the depreciation rate δ . The solid line is for our baseline value of $\delta = 0.1$. The dashed line corresponds to $\delta = 0.2$. As the theory predicts, higher rates of depreciation imply a smaller adjustment of s, S bounds so that the decline in imports is not as pronounced. Intuitively, high depreciation rates limit storage possibilities and therefore, the inventory mechanism in our model becomes less important quantitatively.

If the depreciation rate goes towards 100%, the s, S bounds no longer move in response to an uncertainty shock. Figure A4 illustrates this effect based on a 90% depreciation rate (represented by the dashed line). It can be directly compared to the right panel of Figure A3. Thus, with a very high depreciation rate imports are hardly affected. The inventory mechanism effectively disappears.

A depreciation rate close to 100% could be considered similar to the setting in Alessandria et al. (2010a) in the sense that they model an intermediate retail good that needs to be fully replaced once sold. However, in the latter case the inventory mechanism (driven by first-moment shocks) is still in operation because it works through a desired inventory-to-sales ratio above 1.

Appendix A.3: The Role of First-Moment Shocks The dynamics of imports and inventories in Figures 4 and A3 are driven by changes in the degree of uncertainty. That is, the economy is hit by second-moment shocks only.

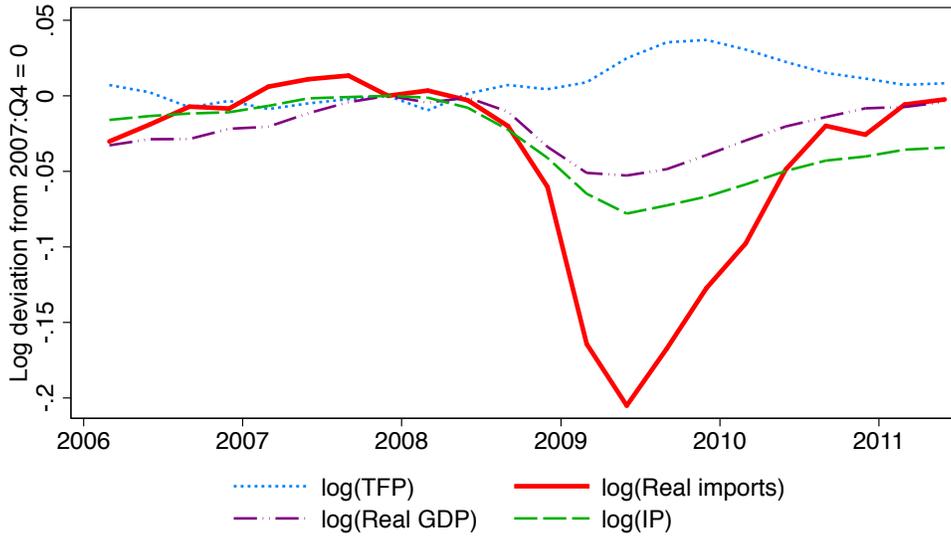
We now consider first-moment shocks. These are shocks to ‘business conditions’ that shift output for either supply-side or demand-side reasons. In our model, the stochastic process (5) describes such shocks. Positive and negative first-moment output shocks at the firm level are normally of equal probability and exactly offset each other so that aggregate output is flat.

To simulate an aggregate first-moment shock, we exogenously change the probabilities of positive and negative shocks. To be precise, we are interested in a 10% negative aggregate output shock. For that purpose we decrease the probability of positive shocks in process (5) by 10% for a period of one month (the probability of receiving no shocks increases commensurately by 10%). After that temporary decrease, the shock probabilities become even again. We leave the degree of uncertainty and the s, S bounds unchanged at their baseline levels (i.e., as in the low-uncertainty state).

We find that imports slide by about 10% and then slowly recover. Most importantly, the first-moment shock does not generate a disproportionate magnification effect. Imports decline in line with the magnitude of the shock (10%). The intuition is that due to the Cobb-Douglas production function (1) and the assumption of fixed input prices, the optimal input-output ratios, K_D/Q and K_F/Q , do not vary over time. Thus, a 10% decline in output translates into an equiproportionate decline in inputs used for production, and through equation (3) into an equiproportionate decline in the target inventory level.

In contrast, in case of a second-moment shock the s, S inventory bounds shift down such that firms run down their inventories longer than usual, leading to more than a proportionate decline in imports. Our framework with second-moment shocks such as in Figure 4 can therefore best be interpreted as explaining the excess volatility of trade flows that arises *in addition* to any first-moment movements, or as explaining the magnified response of trade flows relative to output. Thus, just as with the static gravity model of trade, any such tight linkage between trade and output changes makes trade collapses (relative to output) difficult to explain in terms of first-moment shocks.

Figure A5: U.S. real imports, IP, total factor productivity, and real GDP from 2006:Q1 to 2011:Q4.



Notes: Quarterly data. TFP from the Federal Reserve Bank of San Francisco, utilization adjusted. IP is from the OECD, quarterly. Imports and GDP are from the Bureau of Economic Analysis. Log scale with units set such that the fourth quarter of 2007 is 0.

Arguably, in light of the Great Recession a first-moment demand shock is much more realistic than a supply shock. In the context of our sample, we find no evidence of a large, negative U.S. productivity shock which might account for the observed trade collapse. As the dotted line in Figure A5 shows, during the Great Trade Collapse of 2008 U.S. total factor productivity (TFP) in fact *increased*. Thus, a TFP-based explanation seems unlikely to account for the direction of the Great Trade Collapse, and this in part motivates our decision to focus in this paper on second-moment shocks. Of course, we acknowledge the role of increasing trade barriers, for instance financial frictions, in explaining the trade collapse.

Finally, we note that Alessandria et al. (2010a) also develop an s, S inventory model of trade collapses, with a band of inaction as in our model. However, they only consider first-moment shocks (in particular a negative supply shock) and no second-moment shocks. Yet, in contrast to first-moment shocks in our model, their setting nevertheless generates a decline in imports that exceeds the decline in sales. How? The reason is that their imported input is an intermediate retail good that as a flow variable needs to be fully replaced once sold. When sales of the good take a hit, a multiplier effect kicks in because the firm sells less *and* at the same time starts running down its inventory. As a result, imports are reduced more than one-for-one. (See their example

on p. 273 for an illustration where the firm has a desired inventory-to-sales ratio above 1, leading to a particularly strong degree of magnification.) That is, imports are more volatile than sales due to procyclical inventory investment (Ramey and West 1999).

Unlike in Alessandria et al. (2010a), we generate a disproportionate decline in imports through an endogenous adjustment of s, S inventory bounds caused by second-moment shocks. In our model the imported input is not fully absorbed in the production process. It depreciates by rate δ . (The intermediate retail good in Alessandria et al. (2010a) is storable subject to a depreciation rate, but it is gone once sold.) Our model therefore operates through an entirely different mechanism, via durable capital good inputs, and driven by changes in uncertainty. As we show above, if we let the depreciation rate go towards 100%, the inventory mechanism in our model ceases to operate. Hence, we would no longer be able to explain a trade collapse and subsequent recovery.

It is crucial to note, of course, that we do not dismiss other mechanisms; rather we seek to isolate our new channel for clarity, and to emphasize the original theoretical contribution of this paper. Moreover, in the empirical part of the paper we also provide the first empirical evidence of this channel at work using both aggregate and disaggregated data. In addition, evidence for the model's prediction that the effect of uncertainty shocks is modulated by the durability of the types of goods imported, based on data disaggregated at the industry level.

Appendix A.4: Stockout Avoidance and Asymmetric Loss Function We first explain how stockout avoidance relates to uncertainty, and why our setting gives a different result on inventory holdings compared to Alessandria et al. (2010b). We then comment in more detail on the functional form of our loss function.

Alessandria et al. (2010b) provide micro-foundations for stockout avoidance. They assume that the marginal cost of an additional unit of inventory from the firm's point of view is not the replacement cost it would have to pay in the open market. This would be the relevant marginal cost if delivery were instantaneous. But with a delivery lag, the relevant marginal cost is instead the firm's marginal valuation of an additional unit. This valuation depends on the level of demand. In case of a strong positive demand shock, there would potentially be the risk of a stockout, and the marginal valuation shoots up. The firm deals with this problem by charging customers a sufficiently high price (which is a constant markup over the marginal valuation) such that customers want to buy up just about the entire available stock but no more. Put differently, stockout will never arise because the firm curtails demand accordingly.

It is not clear how inventory holdings would react in that setting in the case of an uncertainty shock with a stochastic process for the second moment. The reason is that the model of Alessandria et al. (2010b) features a first-moment demand shock with a fixed variance and no second-moment shock. Table 5 of Alessandria et al. (2010b) fixes the standard deviation of the demand shock at a constant value (equal to 1.15).

Consistent with Khan and Thomas (2007 *Macroeconomic Dynamics* 11(5), pp. 638–664), it seems plausible that in such models higher uncertainty increases inventory holdings. The reason is that a higher variance of demand shocks increases the likelihood of inventory being depleted.

The nature of uncertainty is different in our setting, however. Higher uncertainty does not mean a higher probability of larger shocks. Higher uncertainty means a higher probability of getting hit by a shock of a given size (as opposed to not being hit at all, see expression 5). Thus, uncertainty in our setting relates to the frequency of shocks, where a shock is a sudden change in business conditions (not being hit by a shock means that business conditions are stable).

Therefore, to explain why all else being equal higher uncertainty initially decreases inventory holdings, the intuition from the literature on uncertainty and the option value of waiting kicks in

(McDonald and Siegel 1986; Dixit 1989; Pindyck 1991). Given the increased probability of getting hit by a shock and thus being forced to adjust, firms have an increased tolerance of running down their inventory (see section 4.2).

How could a stockout avoidance set-up as in Alessandria et al. (2010b) be distinguished from our approach? Suppose we had detailed inventory data at the firm level. In response to a pure second-moment uncertainty shock, a framework such as the one by Alessandria et al. would predict more inventory holdings (which is driven by the stockout avoidance motive). In contrast, our framework would predict fewer inventory holdings (which is driven by the downward shift s, S bounds).

Alessandria et al. (2011) provide evidence from the auto industry showing that in the Great Recession of 2008/09, firms ran down their inventories. Of course, this is in principle consistent with a negative first-moment shock. It would also be consistent with a second-moment shock as in our framework.

The loss function in the context of equation (4) in our model is quadratic and thus symmetric. However, as it is specified in logarithms, when expressed in levels negative deviations from the target are relatively more costly. Losses associated with negative deviations could loosely be seen as the firm's desire to avoid a stockout although this setting is not entirely satisfactory.

To better capture the notion of costly negative deviations as in the stockout avoidance motive, we adopt an asymmetric loss function based on Elliott et al. (2005). That is, we adopt the "generalized loss function" in quadratic terms

$$L_t = [\mu + (1 - 2\mu) \cdot \mathbf{1}(z_t < 0)] z_t^2,$$

where $\mathbf{1}$ is the indicator function and μ is a parameter that governs asymmetry such that we have a quad-quad loss function. Loss aversion corresponds to $0 < \mu < \frac{1}{2}$ when negative deviations incur a disproportionate loss. The special case of $\mu = \frac{1}{2}$ is our baseline symmetric loss function of $\frac{1}{2}z_t^2$.

The asymmetric loss function renders the optimization problem more complicated. We therefore opt to apply it to a simpler version of the model with constant uncertainty (see Hassler

1996, section 2). That is, unlike in expression (6) where the uncertainty process is stochastic and firms anticipate switches from low to high uncertainty and vice versa, we work with a given level of uncertainty λ . We then carry out comparative statics exercises where we vary the degree of asymmetry in the loss function. This provides us with solutions for the s, S bounds as in section 4. As in that section, we solve the model numerically. (It turns out that numerically based on the symmetric loss function, the models with constant and stochastic uncertainty yield quantitatively very similar s, S bounds.)

The Bellman equation for the inventory problem in the constant uncertainty case is

$$V(z_t) = L_t dt + (1 - r dt) E_t V(z_{t+dt}).$$

Setting $dt^2 = 0$ and dividing by dt we arrive at

$$(r + \lambda)V(z_t) + \delta V_z(z_t) = L_t + \lambda (V(S) + f).$$

This is a first-order differential equation. For the indicator function in L_t it is important to note that the return point S and the upper trigger point are positive while the lower trigger point s is negative.

The solution to the differential equation follows as

$$V(z_t) = \left(\frac{2\mu}{r + \lambda} \frac{z_t^2}{2} - \frac{2\mu\delta}{(r + \lambda)^2} z_t + \frac{2\mu\delta^2}{(r + \lambda)^3} + \frac{\lambda f}{r + \lambda} + c_1 e^{-\frac{r+\lambda}{\delta} z_t} \right) + \frac{\lambda}{r} \left(\frac{2\mu}{r + \lambda} \frac{S^2}{2} - \frac{2\mu\delta}{(r + \lambda)^2} S + \frac{2\mu\delta^2}{(r + \lambda)^3} + \frac{\lambda f}{r + \lambda} + c_2 e^{-\frac{r+\lambda}{\delta} S} \right)$$

where c_1 is an integration constant with

$$c_2 = c_1 - \frac{2(1 - 2\mu)\delta^2}{(r + \lambda)^3} \cdot \mathbf{1}(z_t < 0).$$

The derivative of the value function is then given by

$$V_z(z_t) = \frac{2\mu}{r + \lambda} z_t - \frac{2\mu\delta}{(r + \lambda)^2} - \frac{r + \lambda}{\delta} c_1 e^{-\frac{r+\lambda}{\delta} z_t}.$$

Then four conditions describe the solution. The first two are value-matching conditions that link the value at the return point to the values at the lower and upper trigger points:

$$V(S) = V(s) - f,$$

$$V(S) = V(\bar{s}) - f,$$

where \bar{s} denotes the upper trigger point. The final two are smooth-pasting conditions:

$$V_z(S) = 0,$$

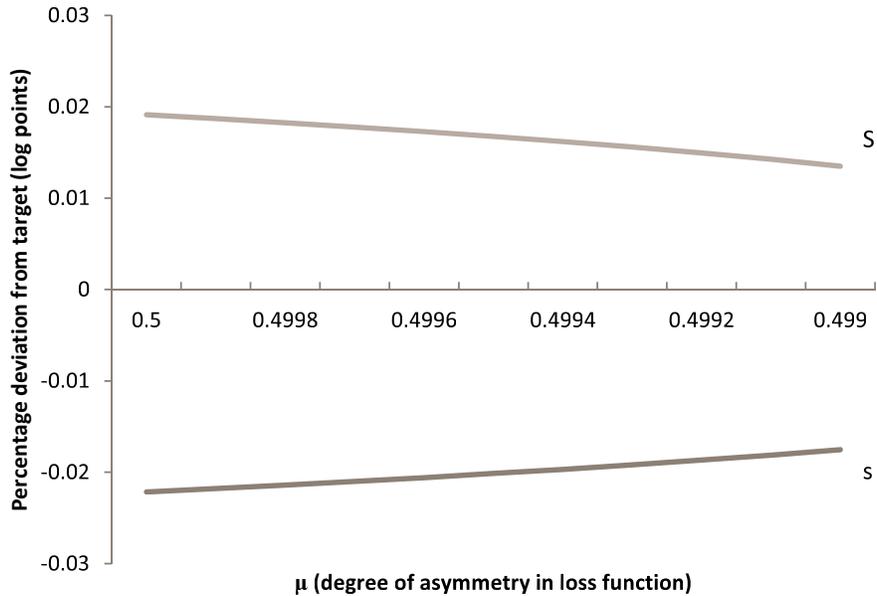
$$V_z(s) = 0.$$

These four conditions pin down the return point, the lower and upper trigger points as well as the integration constant.

We solve the system numerically. For comparability, we retain the same baseline parameterization as in section 4.1, in particular $r = 0.065$, $\delta = 0.1$, $f_F = 0.00005846$ and $\lambda = 1$. Our main aim is to understand how the asymmetry in the loss function affects the s, S bounds. We therefore vary the asymmetry parameter μ and illustrate the bounds graphically in similar fashion to Figure 1. The result can be seen in Figure A6.

The symmetric benchmark corresponds to the value $\mu = 0.5$. When we reduce μ , we introduce an asymmetry in the loss function. It is clear from Figure A6 that the lower the value of μ (i.e., the stronger the loss aversion), the higher the lower trigger point s and the return point S comes down. The intuition is as follows. The rise in the lower trigger point is a straightforward implication of the asymmetric loss function. Negative deviations are less acceptable, and therefore an order is triggered more quickly when inventory runs low. The fall in the return point is linked to the rise in the lower trigger point. As we explain in section 4.2 and as we show in the earlier part of this appendix, in absolute value the lower trigger point deviates further from the target than the return point (a symmetric band around the target would not be optimal). Therefore, as the lower trigger point keeps on rising, the return point must eventually go down. Overall, the bandwidth between the return point and the lower trigger point thus shrinks with rising asymmetry in the

Figure A6: Change in s, S bounds (trigger point, return point) due to a higher degree of asymmetry in the loss function. A smaller value of μ means stronger loss aversion.



loss function.

We also carry out comparative statics with respect to the fixed costs of ordering and the depreciation rate (similar to Figure 3 although not illustrated graphically here). For a lower value of fixed costs, qualitatively this yields the same response to more asymmetry in the loss function as above. That is, the bandwidth between the return point and the lower trigger point shrinks. For a higher depreciation rate, the bandwidth also shrinks. But the shrinking of the bandwidth occurs faster. The intuition is that with a higher depreciation rate, inventory drops more rapidly *ceteris paribus*. The risk of negative deviations from the target is therefore elevated, and the lower trigger point rises in response. Loss aversion reinforces this process.

APPENDIX B: SOURCES FOR DATA USED IN EMPIRICAL ANALYSIS

We follow Bloom (2009, p. 630) and estimate the empirical responses of model quantities to uncertainty shocks using a VAR approach.

Bloom estimates a range of VARs on monthly data from June 1962 to June 2008. In his basic 4-variable system the variables in Cholesky estimation order are log(S&P500 stock market index), the stock-market volatility indicator, log(employment), and log(industrial production). This ordering is based on the assumption that shocks instantaneously influence the stock market (levels and volatility), and only later quantities (hours, employment, and output). Including the stock-market levels as the first variable in the VAR ensures that the impact of stock-market levels is already controlled for when looking at the impact of volatility shocks. All variables are Hodrick-Prescott (HP) detrended ($\lambda = 129,600$) in the VAR estimations, and the same procedure is followed here.

To this empirical framework we make three additions: we extend all data into 2012, we add data for real imports at the aggregate level, and we add data for real imports and industrial production at the disaggregated 4-digit NAICS level, with sources as follows.

S&P500 stock market index: June 1962 to June 2008 from Bloom (2009). Extended through December 2012 with data scraped from <http://finance.yahoo.com>.

Stock-market volatility indicator: June 1962 to June 2008 from Bloom (2009). "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. [...] 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. For the purely exogenous uncertainty shock events, we also use the same definition as in his paper.

Employment, All Manufacturing: June 1962 to June 2008 from Bloom (2009). Extended through December 2012 using the series for All Employees/ Manufacturing (MANEMP) from FRED

<http://research.stlouisfed.org/fred2/>.

Industrial Production, Aggregated: June 1962 to June 2008 from Bloom (2009). Extended from 1919 through December 2012 using the series from G.17 Industrial Production and Capacity Utilization, Board of Governors of the Federal Reserve System.

Real Imports, Aggregated: 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. To obtain real values we deflate by the U.S. series for Consumer Price Index for All Urban Consumers: All Items, Not Seasonally Adjusted (CPIAUCNS), constructed by the U.S. Department of Labor, Bureau of Labor Statistics, and taken from FRED <http://research.stlouisfed.org/fred2/>.

Industrial Production, Disaggregated: 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. Monthly values with data by NAICS 4-digit group and by Fed Market Group. Mapped into End Use categories using a concordance with 2010 gross value added weights also from the G.17 report.

Real Imports, Disaggregated: 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. Mapped into Fed Market Group categories using a concordance. To obtain real values we deflate by the U.S. CPI as above.

APPENDIX C: LIST OF NAICS 4-DIGIT CODES AND DESCRIPTORS

1111	Oilseeds and Grains	3271	Clay and Refractory Products
1112	Vegetables and Melons	3272	Glass and Glass Products
1113	Fruits and Tree Nuts	3273	Cement and Concrete Products
1114	Mushrooms, Nursery and Related Products	3274	Lime and Gypsum Products
1119	Other Agricultural Products	3279	Other Nonmetallic Mineral Products
1121	Cattle	3311	Iron and Steel and Ferroalloy
1122	Swine	3312	Steel Products From Purchased Steel
1123	Poultry and Eggs	3313	Alumina and Aluminum and Processing
1124	Sheep, Goats and Fine Animal Hair	3314	Nonferrous Metal (Except Aluminum) and Processing
1125	Farmed Fish and Related Products	3315	Foundries
1129	Other Animals	3321	Crowns, Closures, Seals and Other Packing Accessories
1132	Forestry Products	3322	Cutlery and Handtools
1133	Timber and Logs	3323	Architectural and Structural Metals
1141	Fish, Fresh, Chilled or Frozen and Other Marine Products	3324	Boilers, Tanks, and Shipping Containers
2111	Oil and Gas	3325	Hardware
2121	Coal and Petroleum Gases	3326	Springs and Wire Products
2122	Metal Ores	3327	Bolts, Nuts, Screws, Rivets, Washers and Other Turned Products
2123	Nonmetallic Minerals	3329	Other Fabricated Metal Products
3111	Animal Foods	3331	Agriculture and Construction Machinery
3112	Grain and Oilseed Milling Products	3332	Industrial Machinery
3113	Sugar and Confectionery Products	3333	Commercial and Service Industry Machinery
3114	Fruit and Vegetable Preserves and Specialty Foods	3334	Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment
3115	Dairy Products	3335	Metalworking Machinery
3116	Meat Products and Meat Packaging Products	3336	Engines, Turbines, and Power Transmission Equipment
3117	Seafood Products Prepared, Canned and Packaged	3339	Other General Purpose Machinery
3118	Bakery and Tortilla Products	3341	Computer Equipment
3119	Foods, NESOI	3342	Communications Equipment
3121	Beverages	3343	Audio and Video Equipment
3122	Tobacco Products	3344	Semiconductors and Other Electronic Components
3131	Fibers, Yarns, and Threads	3345	Navigational, Measuring, Electromedical, and Control Instruments
3132	Fabrics	3346	Magnetic and Optical Media
3133	Finished and Coated Textile Fabrics	3351	Electric Lighting Equipment
3141	Textile Furnishings	3352	Household Appliances and Miscellaneous Machines, NESOI
3149	Other Textile Products	3353	Electrical Equipment
3151	Knit Apparel	3359	Electrical Equipment and Components, NESOI
3152	Apparel	3361	Motor Vehicles
3159	Apparel Accessories	3362	Motor Vehicle Bodies and Trailers
3161	Leather and Hide Tanning	3363	Motor Vehicle Parts
3162	Footwear	3364	Aerospace Products and Parts
3169	Other Leather Products	3365	Railroad Rolling Stock
3211	Sawmill and Wood Products	3366	Ships and Boats
3212	Veneer, Plywood, and Engineered Wood Products	3369	Transportation Equipment, NESOI
3219	Other Wood Products	3371	Household and Institutional Furniture and Kitchen Cabinets
3221	Pulp, Paper, and Paperboard Mill Products	3372	Office Furniture (Including Fixtures)
3222	Converted Paper Products	3379	Furniture Related Products, NESOI
3231	Printed Matter and Related Product, NESOI	3391	Medical Equipment and Supplies
3241	Petroleum and Coal Products	3399	Miscellaneous Manufactured Commodities
3251	Basic Chemicals	5111	Newspapers, Books & Other Published Matter, NESOI
3252	Resin, Synthetic Rubber, & Artificial & Synthetic Fibers & Filament	5112	Software, NESOI
3253	Pesticides, Fertilizers and Other Agricultural Chemicals	5122	Published Printed Music and Music Manuscripts
3254	Pharmaceuticals and Medicines	9100	Waste and Scrap
3255	Paints, Coatings, and Adhesives	9200	Used or Second-Hand Merchandise
3256	Soaps, Cleaning Compounds, and Toilet Preparations	9800	Goods Returned to Canada (Exports Only); U.S. Goods Returned and Reimported Items (Imports Only)
3259	Other Chemical Products and Preparations	9900	Special Classification Provisions, NESOI
3261	Plastics Products		
3262	Rubber Products		

APPENDIX D: IRFs WITH COARSE DISAGGREGATION

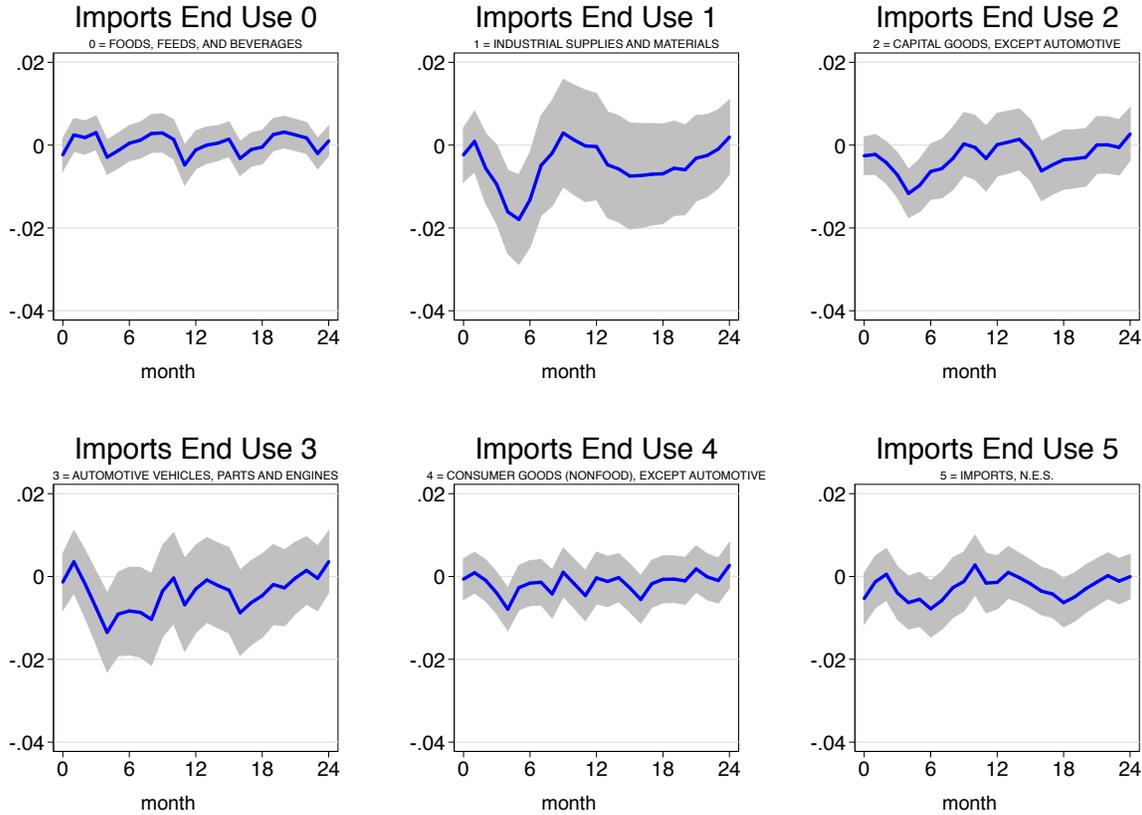
At a coarse level of disaggregation we investigate IRFs for uncertainty shocks when trade and IP data are divided into either End Use categories (a Bureau of Economic Analysis classification) or into Market Groups (a Fed classification). The purpose is to see whether the aggregate result holds up at the sectoral level, and, if 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.

Returning henceforth to the OLS estimation based on the full VXO shock series, Figure D1 shows (non-rescaled) IRFs 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 predictions from theory. There is essentially no response for the most perishable, or least durable, types of goods captured by End Use category 0 (foods, feeds and beverages). This response matches up with cases in our model when the depreciation parameter is set very high. In this case the response to uncertainty shocks diminishes towards zero. Responses are also weak for category 4 (nonfood consumer goods, except automotive), which encompasses nondurable consumer goods, as well as for the residual category 5 (imports not elsewhere specified). In contrast, some sectors show a large response to uncertainty shocks, notably End Use category 1 (industrial supplies and materials), category 2 (capital goods except automotive), and category 3 (automotive vehicles, parts and engines). Category 2, being capital goods, clearly fits with the mechanism we propose, but categories 1 and 3 also include significant durable goods components. 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 mapping from 4-digit NAICS imports to Fed Market Groups (with some weighting using 2002 data on weights).

Figure D2 shows (non-rescaled) IRFs for real imports (upper panel) and IP (lower panel)

Figure D1: *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 quadriariate VARs. Ordering is stock market, volatility, log employment, followed lastly by log real imports. Data updated through February 2012. No rescaling of shocks. 95% confidence intervals shown. See text.

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.

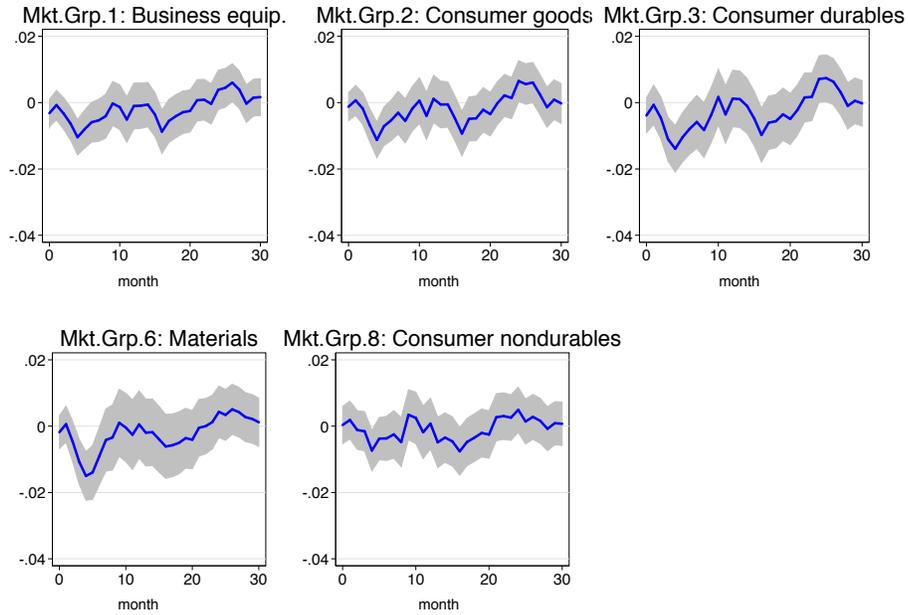
In panel (a) the results for imports are compatible with those above based on End Use categories. Here, in the Fed Market Groups, the largest amplitude responses to an uncertainty shock are seen for materials, business equipment, and consumer durables. The responses show a 1–2 percent drop at peak. The weakest response is for consumer nondurables, which shows about a 0.5 percent drop at peak, although it 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 breach the 95% confidence interval within a range of steps. However,

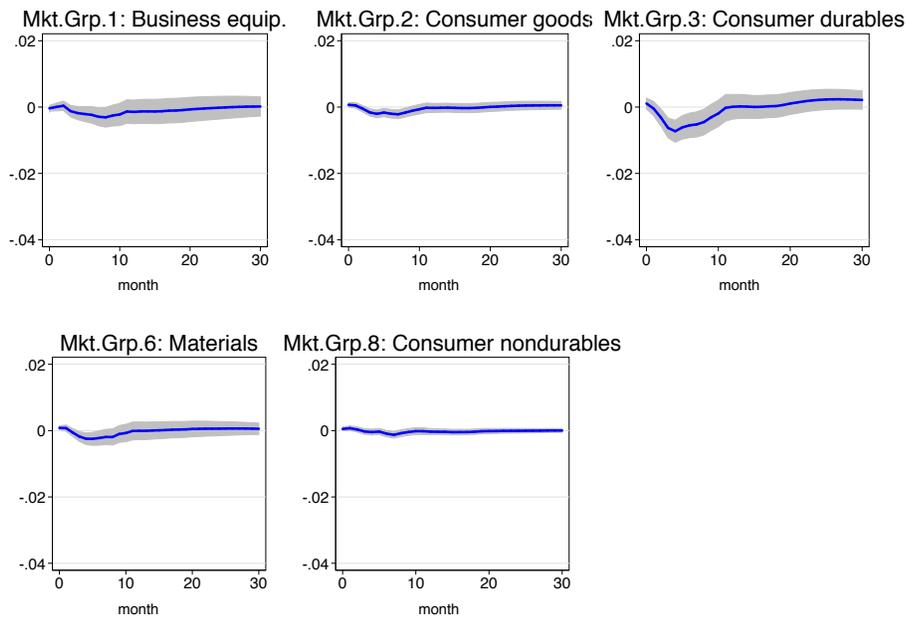
the magnitude of the response is qualitatively different from imports. The consumer durables response is around 0.8 percent at peak for IP, whereas it was almost twice as large, near 1.5 percent, for imports. Materials and business equipment fall at peak by about 0.25 percent for IP, but fell about four times as much in the case of imports. Consumer nondurables in IP are barely perturbed at all.

Figure D2: *Import and IP IRFs by Fed Market Group for uncertainty shocks.*

(a) Real imports



(b) Industrial production



Notes: 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 quadriariate VARs. 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.

APPENDIX E: IRFs WITH FINER DISAGGREGATION

In another robustness check we aim to study dynamic responses to uncertainty shocks at an even finer level of disaggregation, whilst still allowing for an even-handed comparison between import and IP responses in such a way that we can confront the testable predictions of our model.

For this exercise we move to the 3- or 4-digit NAICS level of classification, again sourcing the data 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. A list of NAICS codes at this level of disaggregation, with accompanying descriptors, is provided in the corresponding appendix above. We then aggregate up the quantities to the level of the End Use categories using the Census Bureau concordance.

We estimate every IRF at the End Use level, using the exact same specification as before and repeating the exercise for each NAICS sector with imports and IP.

The End Use categories are:

0 = FOODS, FEEDS, AND BEVERAGES

1 = INDUSTRIAL SUPPLIES AND MATERIALS

2 = CAPITAL GOODS, EXCEPT AUTOMOTIVE

3 = AUTOMOTIVE VEHICLES, PARTS AND ENGINES

4 = CONSUMER GOODS (NONFOOD), EXCEPT AUTOMOTIVE

The resulting cumulative IRFs for months 1–12 are presented in Figure E1.

Overall, a similar pattern of results emerges here, consistent with our previous discussion, whereby the responsiveness to uncertainty shocks tends to be higher for real imports (CPI deflated) than for IP, but we can also see that the effects vary across End Use categories in a manner consistent with our model.

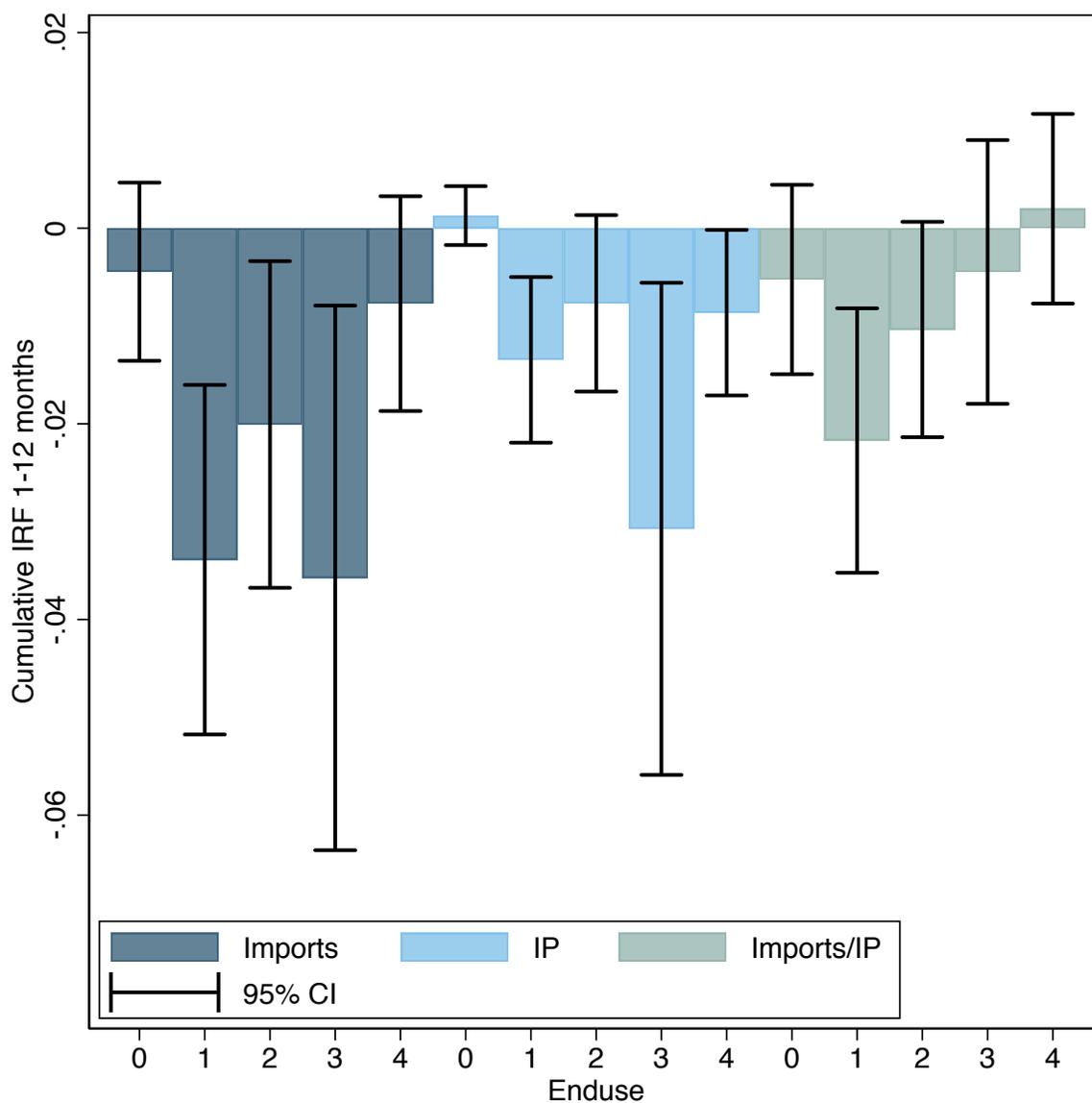
Recall that in our model, three forces operate to make the response to uncertainty shocks high: (a) goods are bought as inputs (inventory), not for final use; (b) goods exhibit more durability; (c) the fixed costs of trade are larger.

The obvious End Use categories which include a lot of durable inputs are End Use 1, 2 and 3, and this is matched by the larger IRFs. We see that with food in End Use category 0, the goods are

more perishable so the effects are smaller here, and this is also matched by the IRFs. Conversely, in End Use categories 1, 2, and 3, the goods are more durable and the effects are bigger.

In particular, our model predicts the largest amplification of import versus IP responses in the cases of goods which are durable and used as inputs, and End Use categories 1 to 3 fit this description: 1 includes potentially storable materials (metals, fuels, plastics, etc.) and the latter is essentially machinery and equipment and some auto parts. By contrast, End Use category 4 is more populated by consumer goods, not inputs.

Figure E1: Average real import and IP IRFs compared in months 1–12 by End Use category



Notes: Cumulative IRF for months 1–12. Flow data at 3- or 4-digit NAICS level, aggregated up to End Use categories using the Census Bureau concordance. 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 quadivariate VARs. 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. See text.

APPENDIX F: ALTERNATIVE MEASURES OF UNCERTAINTY SHOCKS

As a further robustness check, we consider two alternative indices of uncertainty shocks and replicate our baseline result.

The first index we use is the Baker/Bloom/Davis (BBD) text-based measure of “economic policy uncertainty” (see Baker, Bloom and Davis 2016). Their main economic policy uncertainty (EPU) index for the U.S. is available from 1985 monthly. Their Figure VI compares the EPU index to a VIX-based uncertainty measure since 1990. The correlation is 58 percent. Thus, the variation required for our VARs is similar but not the same. The data are available at <http://www.policyuncertainty.com/>.

The second index we use is the Berger/Dew-Becker/Giglio (BDBG) measure of second-moment news shocks (see Berger, Dew-Becker and Giglio 2019). They measure second-moment expectations through the conditional variance of future stock prices (stock returns of the S&P 500 index), aggregated to monthly frequency (see their section 3.1). They construct their uncertainty measure as a residual through VARs (see their section 3.2), and we use their “news” residual (we thank Ian Dew-Becker for sending us this time series).

The three IRF charts in Figures F1-F3 show: 1. the baseline IRFs from the main part of our paper using the Bloom uncertainty index (as a benchmark); 2. the baseline when we replace the Bloom index with BBD; and 3. the same baseline when we replace the Bloom index with BDBG.

The overall message is clear. Though the definitions of the uncertainty shock change, and the sample periods also change somewhat, in quantitative terms the key baseline result stands unchanged. It is always the case that real imports respond much more to uncertainty shocks, as compared to industrial production, by a factor of 4-5 or more.

Figure F1: *Baseline IRFs using Bloom VIX shocks (as reported in Figure 6).*

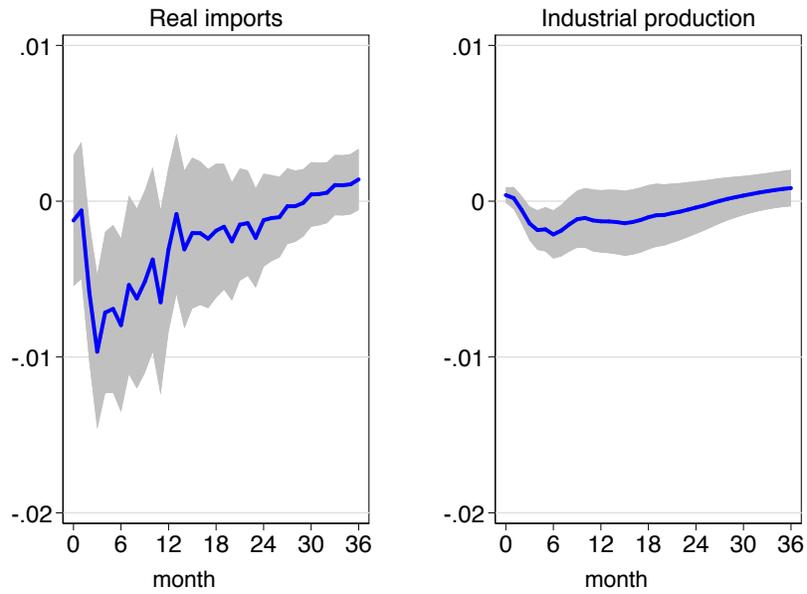


Figure F2: *IRFs using Baker/Bloom/Davis "economic policy uncertainty" shocks.*

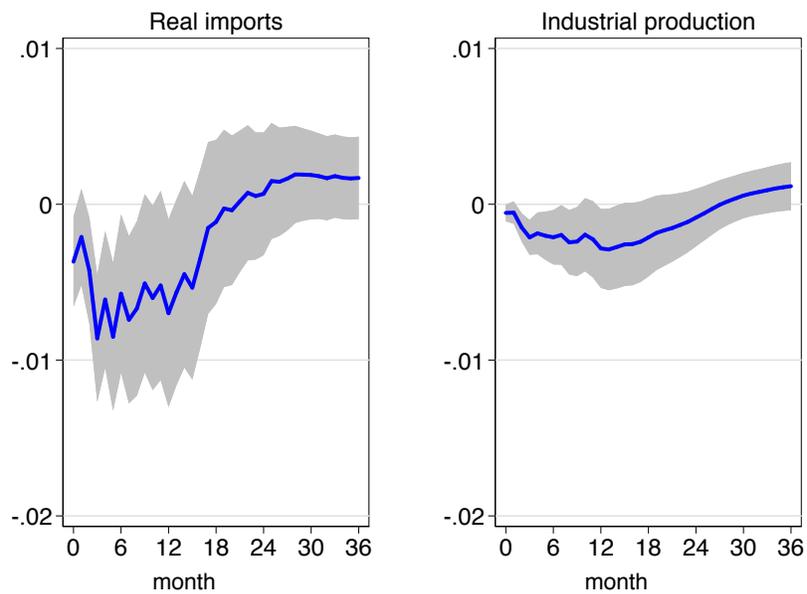
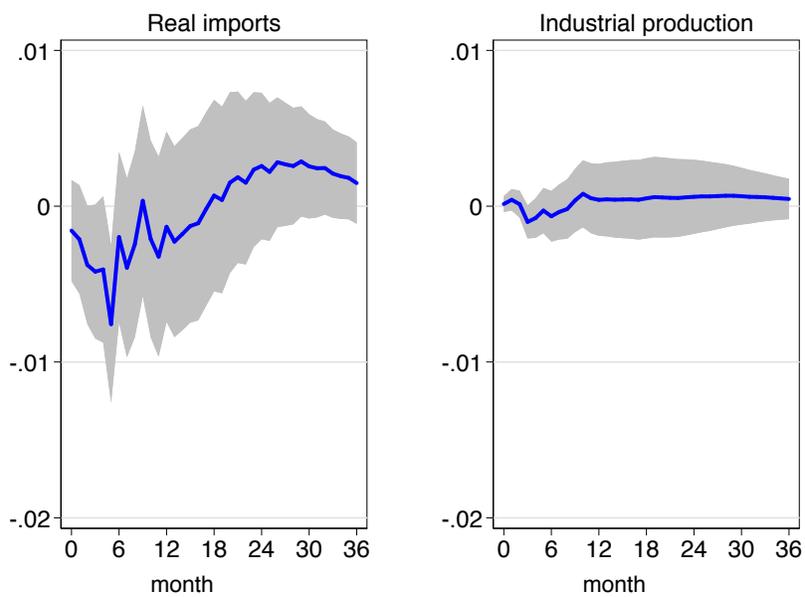


Figure F3: IRFs using Berger/Dew-Becker/Giglio “second-moment news” shocks.



APPENDIX G: CHINA TRADE RELATIONS AS A SECOND-MOMENT SHOCK

To exploit an additional source of variation in the data and to provide a cross-check of our results, we examine the uncertainty associated with annual renewals of China’s Permanent Normal Trade Relations (PNTR) status (cf. Pierce and Schott 2016). We also refer to Handley and Limão (2017) who provide theoretical background and look at trade growth around this episode between 2000 and 2005.

We use a data subset, the monthly U.S. import data from 1989 to 2007 from the U.S. Census Bureau. These data are reported by partner country at the HS₁₀ level (allowing us to isolate China imports). (We thank Robert Feenstra for sharing the relevant data with us.) We then aggregated up to the NAICS₃ level. We found similar results, not shown here, can be seen even at the HS₄ and HS₈ levels.

We then conduct an event analysis experiment using diff-in-diff where we compare U.S. imports from China and the European Union (EU) before and after the 2001 PNTR event. The control group is the EU, the treated group is China, and pre- and post-2001 are the relevant periods. Note that our analysis is with monthly data whereas Pierce and Schott (2016) use annual data. We found similar results, not shown here, can be seen using quarterly aggregation.

Our model can be applied here in the sense that we think of the decrease in uncertainty on China trade after the PNTR event as being like a permanent decrease in demand uncertainty for Chinese goods (e.g., due to the de facto equivalent import-tariff wedge uncertainty falling). Note that the PNTR event did not affect the first moment of tariffs (mean levels), only the second moment.

The regression estimated is

$$\begin{aligned} \log y(i, s, t) = & a(i, s) + b_1(i, s, t) * EU * t + b_2(i, s, t) * CHINA * t \\ & + b_3(i, s, t) * EU * POST * t + b_4(i, s, t) * CHINA * POST * t \\ & + b_5(i, s, t) * CHINA * POST * t^2 + b_6(i, s, t) * CHINA * POST * t^3 \\ & + \zeta(i, s, t), \end{aligned}$$

where y is imports to the U.S. in dollars from each region, with monthly seasonality removed for each region (which is especially needed in the case of China for the New Year). The variable a is the fixed effect for region i , NAICS₃ sector s , and ζ is an error term. The coefficients b_1 to b_4 allow for regional time trends (they differ substantially) pre and post.

The coefficients b_5 and b_6 are the coefficients of interest which capture the post-PNTR differential effect for China which is nonlinear in time, using a cubic trend. Here $POST$ is a dummy for post-PNTR periods and time is scaled so that the month is coded $t = 0$ when PNTR comes into effect. Thus, the import path is restricted to be piecewise continuous at $t = 0$.

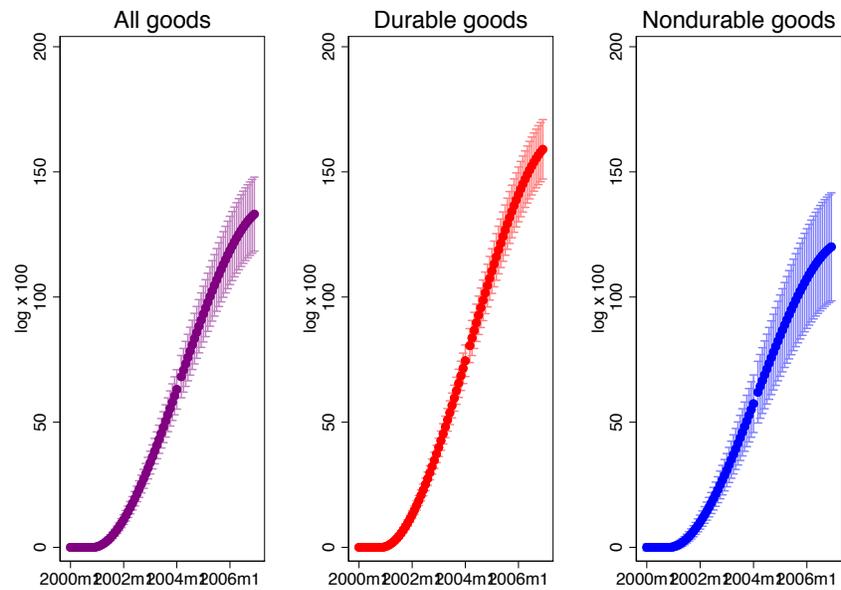
Our model predicts that in response to such a permanent second-moment shock, U.S. imports from China relative to the EU should quickly surge to a high level, but then settle down in the longer term at a somewhat lower level (i.e., we should observe some overshooting relative to the benchmark of a linear trend).

When we plot the fitted values predicted by these b_5 and b_6 coefficients for each bin, holding all other terms at zero, the results shown in the first panel of Figure G1 confirm that we find a pattern of this kind. The acceleration in China-vs-EU imports ramps up but slows down after about 2004, and it peaks at 130 log points in 2006–07. (We would hesitate to draw inferences for post-2008 data, however, given that the onset of the global financial crisis would likely add a lot of noise and possibly potential bias to this outcome variable for reasons outside our model.)

In addition, to examine a further prediction of our model, we can examine whether the patterns differ for durable and nondurable goods by defining a bin indicator variable for durable goods sectors based on Levchenko, Lewis, and Tesar (2010) and then running an augmented specification where we interact that indicator variable with the non-constant terms in the above regression, resulting in separate coefficient estimates b_1 through b_6 for the durable and nondurable bins. (Note that this durable coding is only available at the NAICS₃ level, hence our decision to focus our analysis in this appendix on the NAICS₃ level so that the aggregated and disaggregated results can be compared.)

When we plot the fitted values predicted by the b_5 and b_6 coefficients for each bin (see Table G1), holding all other terms at zero, the results are as shown in the two right panels of Figure G1, where we see that the response of durables is larger than the response of nondurables, consistent

Figure G1: *Fitted values and standard errors for the estimated nonlinear trend component of the log U.S. imports from China relative to EU linear trend post-PNTR based on a cubic trend for each region at the NAICS 3-digit level. See the text for details.*



with our model. (The difference is about 33%, 160 log points log points in 2006–07 versus 120.)

Table G1: Coefficients for the estimated nonlinear trend component of the log U.S. imports from China relative to EU linear trend post-PNTR based on a cubic trend for each region at the NAICS 3-digit level. See the text for details.

	(1)	(2)	
	All goods	Nondurable goods	Durable goods
$CHINA * POST * t^2$	0.0640*** (6.43)	0.0584*** (4.77)	0.0753*** (4.47)
$CHINA * POST * t^3$	-0.000535*** (-5.61)	-0.000492*** (-4.20)	-0.000622*** (-3.87)
N	7526	7526	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$