

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. Firms order inputs from home and foreign suppliers. In response to an uncertainty shock firms disproportionately cut orders of foreign inputs due to higher fixed costs. 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 US import and industrial production data. Our results help to explain the Great Trade Collapse of 2008–2009.

I. 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 twelve months from April 2008, shocks of a magnitude not witnessed since the Great Depression (Eichengreen & 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: standard models of international trade and macroeconomics fail to account for the severity of the events in 2008–2009 now known as the Great Trade Collapse.

As we explain in the next section, 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 examine 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 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 setup, 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 that 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 Hassler's (1996) inventory model with time-varying uncertainty, we show that in response to a large uncertainty shock in business conditions, whether to productivity or the demand for final products, firms 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

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¹See, for example, Campa and Goldberg (1997), Feenstra and Hanson (1999), Eaton and Kortum (2001), and 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.

magnify the response of international trade, given the differential cost structure.

This is a new prediction that 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 US import and industrial production data, some 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 US 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 heavier in durable goods.

To wrap up, we show how our proposed mechanism helps to quantitatively explain a part of the Great Trade Collapse of 2008–2009. 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 while simultaneously controlling for first-moment shocks to business conditions proxied by employment, we show empirically that second-moment shocks have a sizable and independent effect on trade. The result holds also for just the exogenous shocks (terror/war/oil) that Bloom (2009) identified. 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 half

of the unusually large decline in trade in 2008–2009 was in response to this spike in uncertainty.²

Thus, 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 II, we review the literature. In sections III, IV, and V, we outline our theoretical model, do comparative statics, and present simulation results. Section VI presents our empirical evidence. In section VII we ask to what extent uncertainty shocks can empirically account for the recent Great Trade Collapse. Section VIII concludes. We also provide a detailed online appendix.

II. 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, such as 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 it may also be relevant for understanding historical events like the 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 features only 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 & Limão, 2015; Limão & 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

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

³While Bloom (2009) considers US domestic data, Carrière-Swallow and Céspedes (2013) consider domestic data on investment and consumption across forty 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 consider international trade flows.

The Great Trade Collapse of 2008–2009 has been documented by many authors (see Baldwin, 2009, for a collection of approaches, and Bems, Johnson, & Yi, 2013, for a survey). Eaton et al. (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 et al. (2013). More specifically, Kee, Neagu, and Nicita (2013) find that less than 2% 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 that experienced economic difficulties.

Amiti and Weinstein (2011) and Chor and Manova (2012) highlight the role of financial frictions and the drying up of trade credit. However, based on evidence from Italian manufacturing firms, Guiso and Parigi (1999) show that the negative effect of uncertainty on investment cannot be explained by liquidity constraints. 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 toward 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 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 & 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 US data, heightened uncertainty stands out as a defining feature of the Great Recession, and we employ an observable measure of it. However, as we show, there is little evidence in the US data of a major first-moment TFP shock coincident with the onset of the crisis.

Finally, Alessandria et al. (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 versus nonexporters. Intuitively, exporters tend to be at the upper tail of the productivity distribution. Increases in the dispersion of productivity shocks thus confer an even greater advantage to exporters compared to nonexporters.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.

III. 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 or demand, or both. 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.

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.

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."

A. 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.

B. 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 four-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. Because 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, equation (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 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

$$m_D^* = c_D + q, \quad (3)$$

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 0 deviation. However, since we assume positive ordering 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 ,

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) barely changed during the Great Trade Collapse of 2008–2009. 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 nondifferentiated manufactures decreased considerably. In the empirical part of the paper 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.

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, & Mion, 2013; Bricongne et al., 2012), we do not model firms’ switching from a foreign to a domestic supplier, or vice versa. As we discuss in section V, this would arguably reinforce the negative impact of uncertainty shocks on imports.

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.

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).

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 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 depreciates only if used in production, not if it is merely in storage as inventory.

C. 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 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 of equation (5) has a *first moment* equal to 0 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 their size. Higher uncertainty here does not mean an increased probability of larger shocks.

Specifically, as the simplest possible setup, 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 by equations (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 .

IV. 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

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.

¹²Hassler (1996, sec. 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 V 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 0. 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.

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 (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 volatility of a geometric random walk.

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.

A. Parameterizing the Model

We choose the same parameter values for the interest rate and rate of depreciation as Bloom (2009): $r = 0.065$ and $\delta = 0.1$ per year. The interest rate value corresponds to the long-run average for the US firm-level discount rate. Based on data for the US 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 two months. This information can be expressed in terms of the transition probabilities in equation (6) 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 $\frac{2}{12}$ 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 seventeen uncertainty shocks in 46 years. Hence, an uncertainty shock arrives on average every $\frac{46}{17} = 2.7059$ 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, equation (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 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 US 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 might be considered more realistic.

B. 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

¹⁵For a given λ , the conditional variance of process (5) is proportional to λ so that the 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 et al. (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 microlevel 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 GRAY, THE HIGH-UNCERTAINTY STATE IN BLACK.

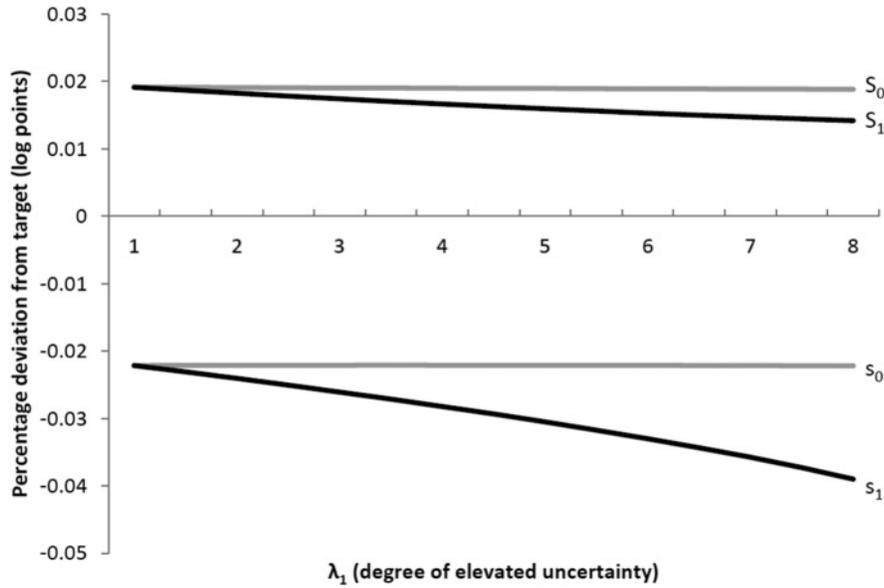
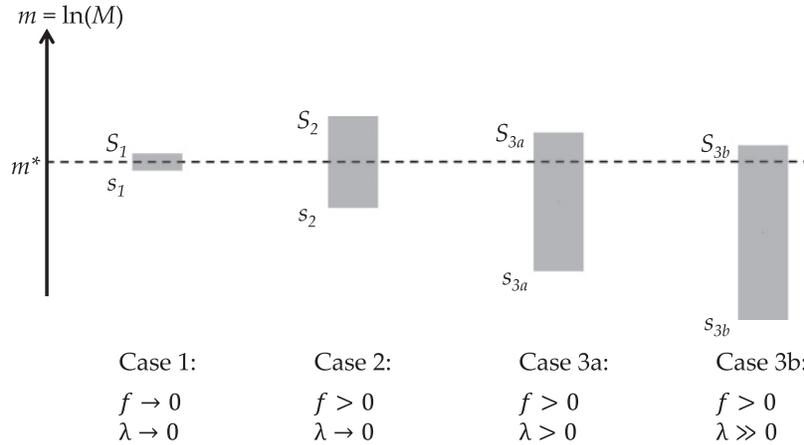


FIGURE 2.—SUMMARY: HOW UNCERTAINTY PUSHES DOWN THE s , S BOUNDS AND INCREASES THE BANDWIDTH



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 .

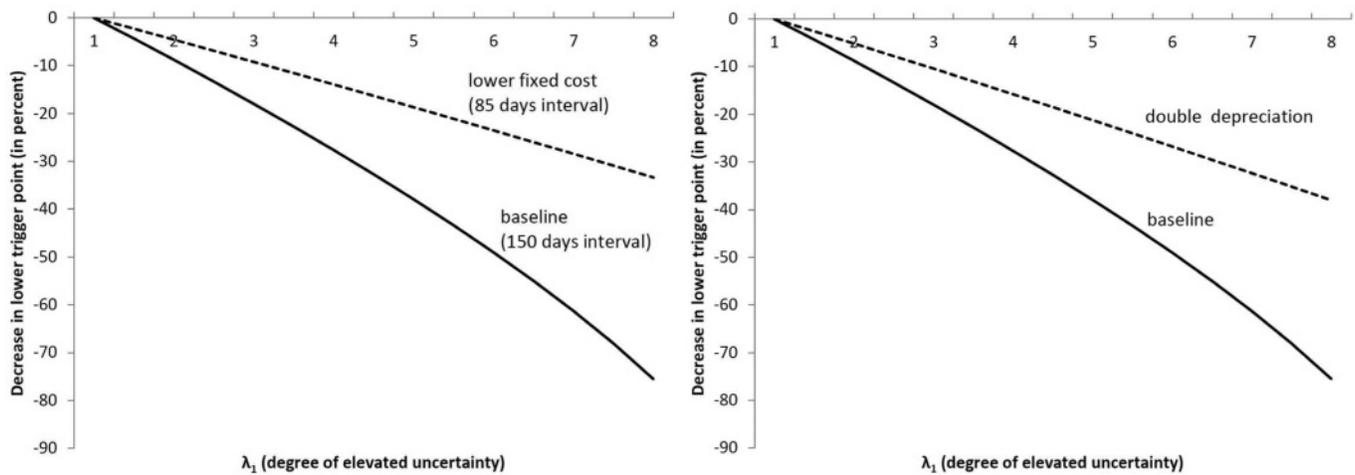
Two observations stand out. First, the lower trigger point always deviates farther from the target than the return point. This is true for both states of uncertainty (i.e., $|s_0| > S_0$ and $|s_1| > S_1$). As we show in the theory appendix, in the presence of uncertainty, a symmetric band around the target (i.e., $|s_\omega| = S_0$) would not be optimal. The reason is 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, that is, $\partial S_1 / \partial \lambda_1 < 0$ 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 & 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^* .

FIGURE 3.—THE EFFECT OF LOWER FIXED COSTS (LEFT) AND A HIGHER DEPRECIATION RATE (RIGHT) ON THE DECREASE IN THE LOWER TRIGGER POINT



In case 2, the fixed costs become larger, which pushes both s_1 and S_1 farther away from the target but in a symmetric way. Cases 3a and 3b correspond to the situation we consider in this paper with nonnegligible 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.

C. Comparative Statics

We have assumed fixed costs of ordering to be lower when the input is ordered domestically: $f_D < f_F$. 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.

V. 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 IVA, and we focus on the foreign-sourced input K_F and the associated fixed costs f_F .

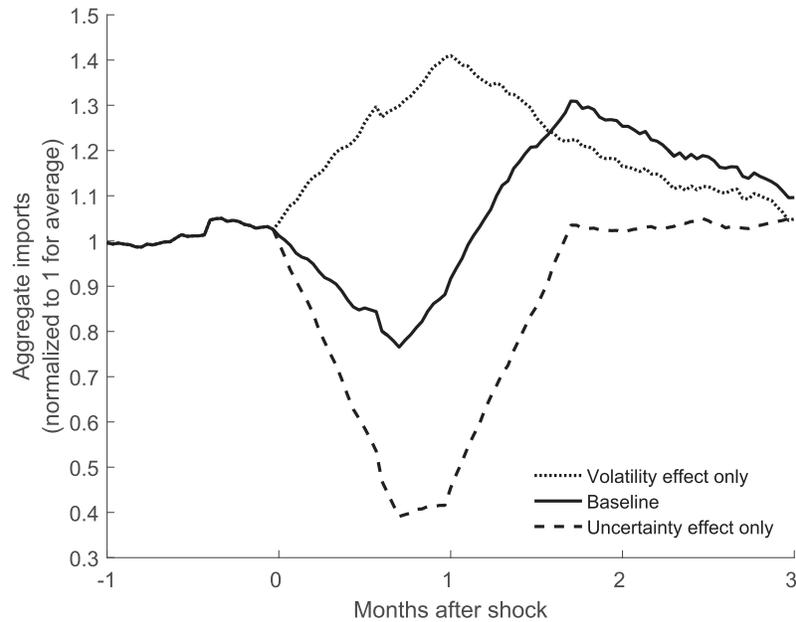
We simulate an uncertainty shock by permanently shifting the economy from low uncertainty λ_0 to high uncertainty λ_1 . A key result from section IVB is that firms lower their s , S bounds in response to increased uncertainty. This shift leads to a strong downward adjustment of input inventories and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

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



instance, during the Great Recession, German imports peaked in the second quarter of 2008, rapidly declined by 32%, and returned to their previous level only by the third quarter of 2011.¹⁷ Greater persistence could be 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, that is, 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 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 in section VII.

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.

VI. 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 of uncertainty, production, and international trade

¹⁷Most high-income countries experienced similar patterns. US and Japanese imports 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 2008–2009 recession, Behrens et al. (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 et al. (2010) present similar evidence for US imports, which we consider in our empirical analysis.

by estimating vector autoregressions (VARs) with US 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 that 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 Moreover, 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, while 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 since the onset of the Great Recession has flared again as an object of curiosity and worry to scholars and policymakers alike.

A. 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 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 section briefly spells out the empirical VAR methods we employ. The second section spells out the data we have at our disposal, some newly collected, to examine the differences between trade and industrial production in this framework. The subsequent sections discuss our findings.

B. Computing the Responses to an Uncertainty Shock

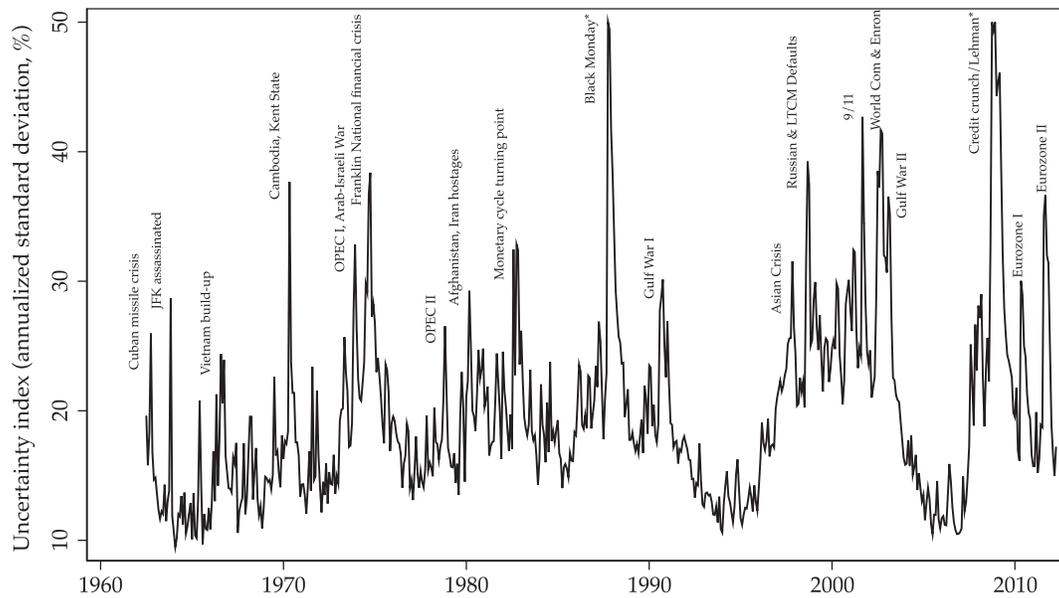
In typical business cycle empirical work, researchers are often interested in the response of key variables, most of all output, to various shocks, most often a shock to the level of technology or productivity. The analysis of such first-moment shocks has long been a centerpiece of the macroeconomic VAR literature. Bloom’s (2009) innovation 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 United States, changes in the VXO US 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 thirty-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

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 thank Nicholas Bloom for providing us with an updated series extended to 2012.

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

FIGURE 5.—THE UNCERTAINTY INDEX: MONTHLY US STOCK MARKET VOLATILITY, 1962–2012



VXO index and proxies. Capped at 50 (*). From Bloom (2009) and updates. See the appendix.

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

C. 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&P 500 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.

- US 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.
- US disaggregated monthly real imports. These data run only from 1989:1 to 2012:2. In each month, total imports for general consumption disaggregated at the four-digit NAICS level were obtained from the USITC dataweb.

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.”

All series were then deflated by the monthly CPI. In this way, 108 sector-level monthly real import series were compiled.

- US disaggregated monthly industrial production. These data run only 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 start only 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 four-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.

D. IRFs at Aggregate Level for Trade and IP

The world witnessed an unusually steep decline in international trade in 2008–2009, 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) 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 US 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 quadripartite VAR results for the aggregate US 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). 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 five to ten times as strong on average in the period of peak impact during year 1. The response of imports is also highly statistically significant. At its peak, the IRF is 3 or 4 standard

errors below 0, whereas the IRF for IP is only just about 2 standard errors below 0, 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 0.

To provide further evidence and a robustness check, consider 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 of 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 (2020).

E. 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 three- or four-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 reestimate 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.

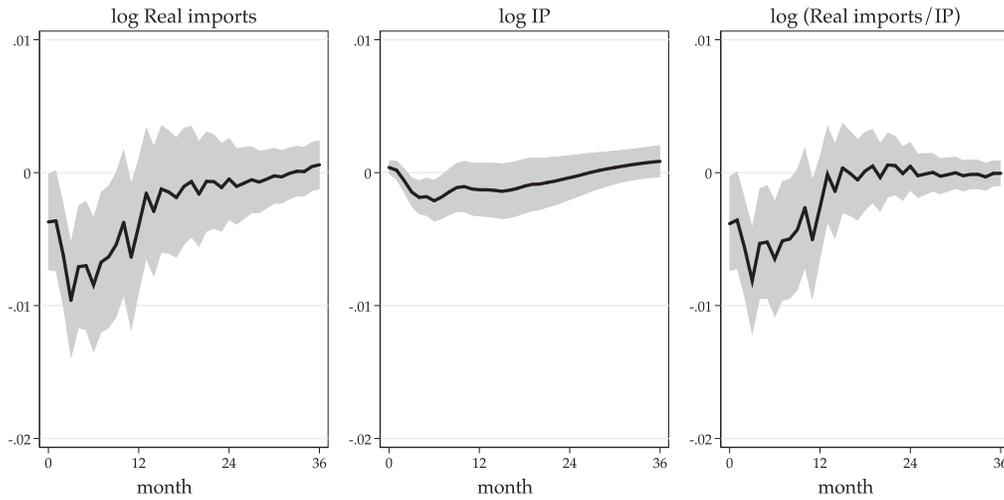
To offer a presentation of the results in a way that corresponds to the durable-nondurable distinction, we then aggregate up the IRFs into two bins, corresponding to durable and nondurable manufacturing sectors, according to the NAICS classification of sectors by the BLS.²³ The resulting weighted average IRFs for months 1 to 12 are presented as summary statistics in figure 7. The correspondence between the

²²Virtually identical results, available on request, are produced when the unscaled shock is used. Specifically, Bloom (2009) identifies seventeen 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.

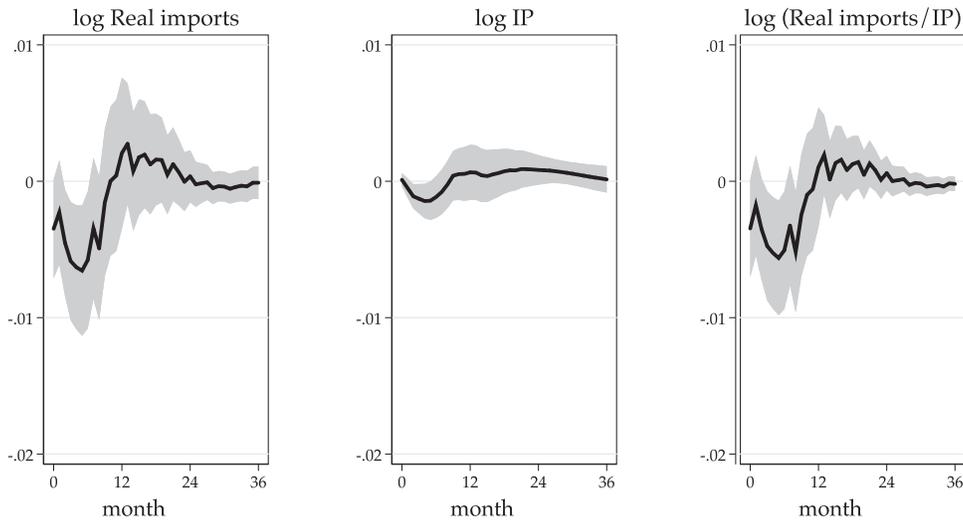
²³See <https://www.bls.gov/jlt/jltnaics.htm>.

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.*



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

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 (two times). In both cases, the responses in real imports are larger than in IP (two 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 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.

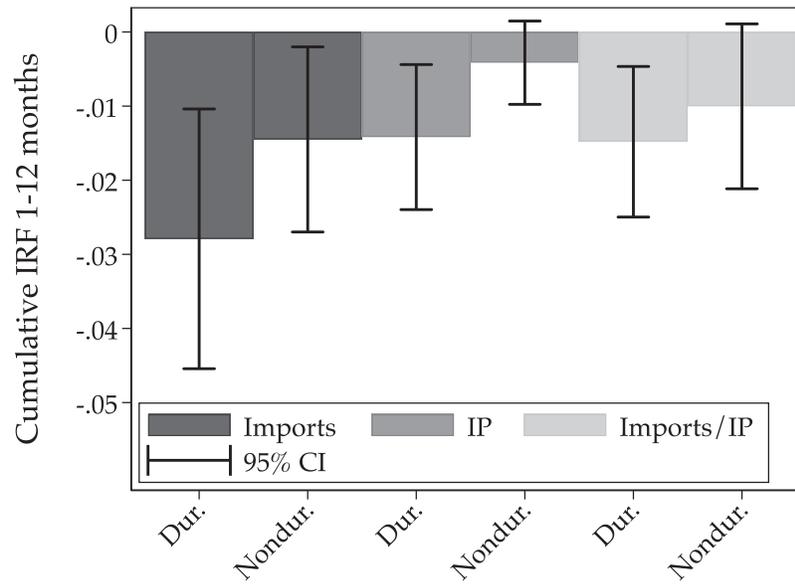
Finally, we refer to the appendix where we provide additional robustness checks exploiting the granting of Permanent Normal Trade Relations (PNTR) status to China (see Pierce & Schott, 2016; Handley & Limão, 2017). There we employ US import data from China and the European Union at the four-digit level.

F. 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

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 THREE- OR FOUR-DIGIT NAICS LEVEL



Cumulative IRF for months 1–12. Flow data at the three- or four-digit NAICS level, aggregated up to BLS durable-nondurable bins for manufacturing industries using output weights from the Fed's US 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 multivariate VARs. Ordering is stock market, volatility, log employment, followed by either log real imports or log IP. Data updated through February 2012. No rescaling of shocks. See text and appendix.

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 US 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 that would affect firms trying to export from that source to the United States.

Figure 8 contains the results of this exercise, conducted on the sample period 1989:1 to 2012:12. The left panel shows that US 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 the confidence intervals in the two panels overlap quantitatively.

VII. Can the Great Trade Collapse of 2008–2009 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, pro-

vide a *quantitatively* plausible account of the Great Trade Collapse of 2008–2009?

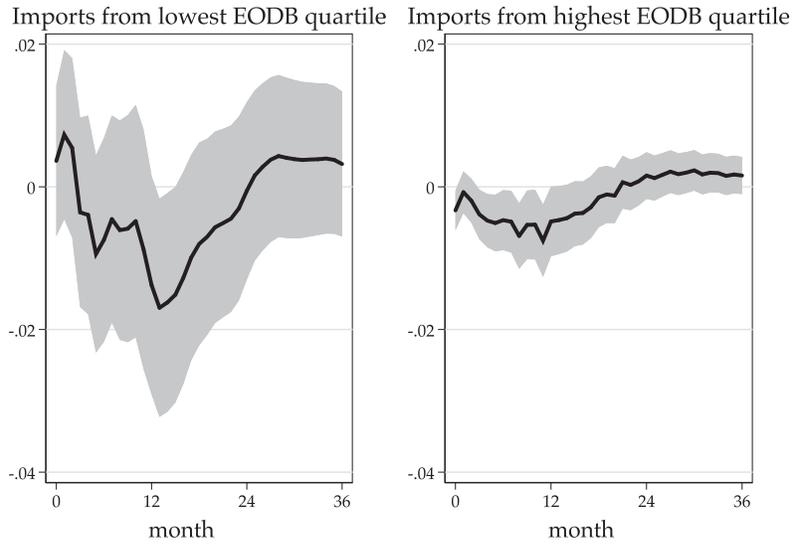
We thus conclude by presenting a simulation exercise, using our baseline aggregate VAR from section VI, to argue that this mechanism could indeed have been an important contributing factor, even if other forces were in play. To do this, we need to construct a set of plausible exogenous shocks to the 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 that 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 from 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 that generate a path of volatility similar to that observed. 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 of 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

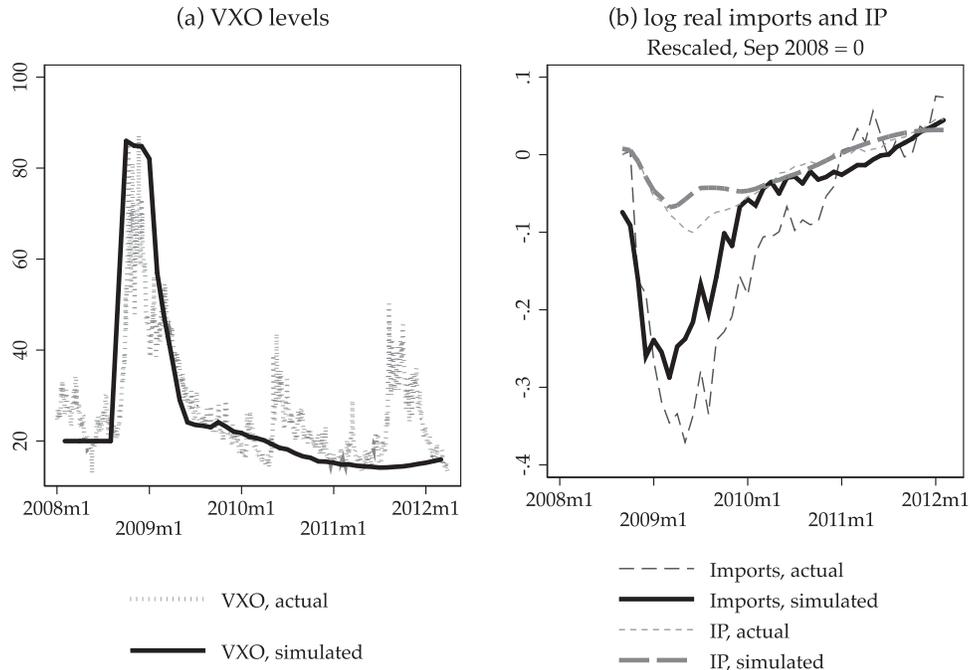
²⁵See <http://www.doingbusiness.org/rankings>.

FIGURE 8.—IRFs AT AGGREGATE LEVEL FOR HIGH- AND LOW-FIXED COST SOURCE COUNTRIES (LOW AND HIGH EODB, RESPECTIVELY)



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

FIGURE 9.—ACTUAL AND SIMULATED VXO, REAL IMPORTS, AND IP DURING AND AFTER THE 2008 LEHMAN UNCERTAINTY SHOCK



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 precrisis 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 six 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 twelve-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 II).

In their survey of that literature, Bems et al. (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% to 80% 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% to 20% are due to credit supply shocks. Inventory adjustments as an amplification mechanism may account for around 20%.²⁶ Our work suggests that the latter share may be larger because of second-moment shocks, not least since inventories are relevant for both intermediate and final goods. But a precise decomposition is yet to be carried out and remains as an important topic for future work. Finally, 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.

VIII. 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, which 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 substantial heterogeneity in responses at the sectoral level, for both 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 2008–2009, 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.

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²⁶These estimates do not necessarily sum up to 100% since they are obtained from independent papers.

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