Appendix A: Theory Appendix

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

\[ V(z_t, \omega_t) = \frac{1}{2}z_t^2 dt + (1 - rd_t)E_tV(z_{t+dt}, \omega_{t+dt}). \]  \hspace{1cm} (A1)

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

\[ E_tV(z_{t+dt}, \omega_{t+dt}) = V_z(z_t, \omega_t) - \delta dt V_z(z_t, \omega_t) \]
\[ + \lambda_\omega dt \left\{ V(S_\omega, \omega_t) + f - V(z_t, \omega_t) \right\} \]
\[ + \gamma_\omega dt \left\{ V(z_t, \omega_t) - V(z_t, \omega_t) \right\}, \]  \hspace{1cm} (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 \( \delta \). 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 \( S_\omega \)), as well as the probability \( \gamma_\omega dt \) that the uncertainty state switches from \( \omega_t \) to \( \bar{\omega}_t \).

Equations (A1) and (A2) form a system of two differential equations for the two possible states \( \omega_t \) 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 \( \lambda_0 \), and the bounds \( s_1 \) and \( S_1 \) for the state of high uncertainty \( \lambda_1 \). It turns out that in either state \( \omega \), the cost function \( V \) reaches its lowest level at the respective return point \( S_\omega \). 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:

\[
rV(z_t, \omega_t) = \frac{1}{2} z_t^2 - \delta V_z(z_t, \omega_t) + \lambda_\omega \left\{ V(S_{\omega}, \omega_t) + f - V(z_t, \omega_t) \right\} + \gamma_\omega \left\{ V(z_t, \overline{\omega}_t) - V(z_t, \omega_t) \right\}.
\]

The set of solutions to this system is given by

\[
V(z_t, 0) = \frac{a_0}{2} z_t^2 + \beta_0 z_t + c_1 e^{\rho_1 z_t} + c_2 e^{\rho_2 z_t} + \phi_0 + \frac{1}{\Delta} \left\{ \lambda_1 \psi_0 V(S_1, 1) + \lambda_0 \psi_1 V(S_0, 0) \right\} \quad (A3)
\]

for the state of low uncertainty, and

\[
V(z_t, 1) = \frac{a_1}{2} z_t^2 + \beta_1 z_t + v_1 c_1 e^{\rho_1 z_t} + v_2 c_2 e^{\rho_2 z_t} + \phi_1 + \frac{1}{\Delta} \left\{ \lambda_1 \psi_0 V(S_1, 1) + \lambda_0 \psi_1 V(S_0, 0) \right\} \quad (A4)
\]

for the state of high uncertainty, where \( c_1 \) and \( c_2 \) are the integration constants. The parameters \( \psi_0, \psi_1, \Delta, a_0, a_1, \beta_0, \beta_1, \phi_0 \) and \( \phi_1 \) are given by

\[
\psi_\omega = r + \lambda_\omega + \gamma_\omega, \\
\Delta = \psi_0 \psi_1 - \gamma_0 \gamma_1, \\
a_\omega = \frac{1}{\Delta} (r + \lambda_\omega + \gamma_\omega + \gamma_\omega), \\
\beta_\omega = -\frac{\delta}{\Delta} (\psi_\omega a_\omega + \gamma_\omega a_\omega), \\
\phi_\omega = \frac{1}{\Delta} (\psi_\omega (\lambda_\omega f - \delta \beta_\omega) + \gamma_\omega (\lambda_\omega f - \delta \beta_\omega)),
\]

where \( \overline{\omega} = 1 \) if \( \omega = 0 \), and vice versa. \([v_i, 1]'\) is the eigenvector that corresponds to the eigenvalue \( \rho_i \) 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):

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

This expression can be shown to be strictly positive since each term is positive: $(r + \lambda_\omega) f > 0$ and, moreover, $\gamma_\omega \{ f - (V(s_\omega, \overline{w}_t) - V(S_\omega, \overline{w}_t)) \} \geq 0$. 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 $S_\omega$. That is, for any $z_t$ the cost value $V(z_t, \overline{w}_t)$ can never exceed the minimum value $V(S_\omega, \overline{w}_t) + f$. It therefore also follows that $V(s_\omega, \overline{w}_t)$ can never exceed $V(S_\omega, \overline{w}_t) + f$, i.e., $V(s_\omega, \overline{w}_t) \leq V(S_\omega, \overline{w}_t) + f$. 

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Recall that the lower trigger point $s_\omega$ is expressed as a deviation from the target level $m^*$. We therefore have $s_\omega < 0$. Conversely, the return point $S_\omega$ 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 $S_\omega$. 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 $\lambda_0$). 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 $\lambda_1$ from $\lambda_0$ 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 $\varepsilon$ 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 $\lambda_1$ 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 $\epsilon$ 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 $\lambda_0$ after two months as opposed to staying permanently high at $\lambda_1$. 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
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 $\delta$. 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 equiproporionate 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 \( \delta \). (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 [3]). 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

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

where $1$ is the indicator function and $\mu$ 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 \( \lambda \). 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

\[
V(z_t) = L_t \, dt + (1 - rd_t) E_t V(z_{t+dt}).
\]

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

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

where \( c_1 \) is an integration constant with

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

The derivative of the value function is then given by

\[
V_z(z_t) = \frac{2\mu}{r + \lambda} z_t - \frac{2\mu\delta}{(r + \lambda)^2} - \frac{r + \lambda}{\delta} c_1 e^{-\frac{r + \lambda}{2} z_t}.
\]
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 \( \mu \) 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 \( \mu \), we introduce an asymmetry in the loss function. It is clear from Figure A6 that the lower the value of \( \mu \) (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
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.
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.


**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. [... M]onthly 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

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  Olives and Grapes
1112  Vegetables and Melons
1113  Fruits and Tree Nuts
1114  Mushrooms, Nursery and Related Products
1115  Other Agricultural Products
1119  Cattle
1121  Swine
1122  Wool
1123  Poultry and Eggs
1124  Sheep, Goats and Fine Animal Hair
1125  Farmed Fish and Related Products
1129  Other Animals
1132  Forestry Products
1133  Timber and Logs
1141  Fish, Fresh, Chilled or Frozen and Other Marine Products
2111  Oil and Gas
2112  Coal and Petroleum Gases
2121  Metal Ores
2122  Nonferrous Minerals
3111  Animal Foods
3112  Grain and Oilseed Milling Products
3113  Sugar and Confectionery Products
3114  Fruit and Vegetable Preserves and Specialty Foods
3115  Dairy Products
3116  Meat Products and Meat Packaging Products
3117  Seafood Products Prepared, Canned and Packaged
3118  Bakery and Tortilla Products
3119  Other Foods, NESOI
3121  Beverages
3122  Tobacco Products
3131  Fibers, Yarns, and Threads
3132  Fabrics
3133  Finished and Coated Textile Fabrics
3141  Textile Furnishings
3149  Other Textile Products
3151  Knit Apparel
3152  Apparel
3159  Apparel Accessories
3161  Leather and Hide Tanning
3162  Footwear
3169  Other Leather Products
3211  Sawmill and Wood Products
3212  Veneer, Plywood, and Engineered Wood Products
3219  Other Wood Products
3221  Pulp, Paper, and Paperboard Mill Products
3222  Converted Paper Products
3231  Printed Matter and Related Product, NESOI
3241  Petroleum and Coal Products
3251  Basic Chemicals
3252  Resin, Synthetic Rubber, & Artificial & Synthetic Fibers & Filament
3253  Pesticides, Fertilizers and Other Agricultural Chemicals
3254  Pharmaceuticals and Medicines
3255  Paints, Coatings, and Adhesives
3259  Other Chemical Products and Preparations
3261  Plastics Products
3262  Rubber Products
3269  Other Nonmetallic Minerals
3271  Clay and Refractory Products
3272  Glass and Glass Products
3273  Cement and Concrete Products
3274  Lime and Gypsum Products
3279  Other Nonmetallic Mineral Products
3291  Iron and Steel and Ferroalloy
3312  Steel Products From Purchased Steel
3313  Alumina and Aluminum and Processing
3314  Nonferrous Metal (Except Aluminum) and Processing
3315  Foundries
3321  Crowns, Closures, Seals and Other Packing Accessories
3322  Cutlery and Handtools
3323  Architectural and Structural Metals
3324  Boilers, Tanks, and Shipping Containers
3325  Hardware
3326  Springs and Wire Products
3327  Bolts, Nuts, Screws, Rivets, Washers and Other Turned Products
3328  Other Fabricated Metal Products
3331  Agriculture and Construction Machinery
3332  Industrial Machinery
3333  Commercial and Service Industry Machinery
3334  Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment
3335  Metalworking Machinery
3336  Engines, Turbines, and Power Transmission Equipment
3339  Other General Purpose Machinery
3341  Computer Equipment
3342  Communications Equipment
3343  Audio and Video Equipment
3344  Semiconductors and Other Electronic Components
3345  Navigational, Measuring, Electromedical, and Control Instruments
3346  Magnetic and Optical Media
3351  Electric Lighting Equipment
3352  Household Appliances and Miscellaneous Machines, NESOI
3353  Electrical Equipment
3355  Electrical Equipment and Components, NESOI
3361  Motor Vehicles
3362  Motor Vehicle Bodies and Trailers
3363  Motor Vehicle Parts
3364  Aerospace Products and Parts
3365  Railroad Rolling Stock
3366  Ships and Boats
3369  Transportation Equipment, NESOI
3371  Household and Institutional Furniture and Kitchen Cabinets
3372  Office Furniture (Including Fixtures)
3379  Furniture Related Products, NESOI
3391  Medical Equipment and Supplies
3399  Miscellaneous Manufactured Commodities
3411  Newspapers, Books & Other Published Matter, NESOI
3412  Software, NESOI
3415  Printed Music and Music Manuscripts
3420  Used or Second-Hand Merchandise
9000  Goods Returned to Canada (Exports Only); U.S. Goods Returned and Reimported Items (Imports Only)
9001  Waste and Scrap
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 quadvariate 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 quadvariate 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 quadvariate 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

$$
\log y(i, s, t) = a(i, s) + b_1(i, s, t) \times EU \ast t + b_2(i, s, t) \times CHINA \ast t \\
+ b_3(i, s, t) \times EU \times POST \times t + b_4(i, s, t) \times CHINA \times POST \times t \\
+ b_5(i, s, t) \times CHINA \times POST \times t^2 + b_6(i, s, t) \times CHINA \times POST \times t^3 \\
+ \xi(i, s, t),
$$
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 $\xi$ 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.

<table>
<thead>
<tr>
<th></th>
<th>All goods</th>
<th>Nondurable goods</th>
<th>Durable goods</th>
</tr>
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<tr>
<td>( CHINA^{<em>}POST^{</em>}t^2 )</td>
<td>0.0640***</td>
<td>0.0584***</td>
<td>0.0753***</td>
</tr>
<tr>
<td></td>
<td>(6.43)</td>
<td>(4.77)</td>
<td>(4.47)</td>
</tr>
<tr>
<td>( CHINA^{<em>}POST^{</em>}t^3 )</td>
<td>-0.000535***</td>
<td>-0.000492***</td>
<td>-0.000622***</td>
</tr>
<tr>
<td></td>
<td>(-5.61)</td>
<td>(-4.20)</td>
<td>(-3.87)</td>
</tr>
<tr>
<td>( N )</td>
<td>7526</td>
<td>7526</td>
<td></td>
</tr>
</tbody>
</table>

* \( t \) statistics in parentheses
* * \( p < 0.05, ** p < 0.01, *** p < 0.001 \)