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The bullwhip effect and the Great Trade Collapse

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Summary
This paper demonstrates the bullwhip effect in a simple framework and tests its predictions using US industry level import data. I show that after final goods suffer a demand shock, upstream suppliers face a greater volatility of sales than their downstream counterparts and might even lose sales temporarily. The effect of the shock is magnified when the inventory-to-sales ratio of the industry is high. The impact can turn non-monotonic, that is, the volatility of a downstream production stage might exceed the volatility of its suppliers, if the upstream producers operate in networks of chains with uncorrelated demands. I show empirically that, in line with the bullwhip effect, the volatility of US imports after the Lehman shock is higher for upstream industries. In addition, upstream products are more likely to drop out of trading completely. Most of the dropouts, however, are temporary and about 90 per cent of products return to trading within two years after the shock. Those imports that do not return are more likely to have been traded for a shorter period and in smaller quantities pre-crisis.

Keywords: trade collapse, supply chains, bullwhip effect.

JEL Classification: F15, F23, L22.

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1 Introduction

The period after the Lehman Brothers bankruptcy in late 2008 and early 2009 was characterised by an enormous increase in the volatility of trade. After an extreme drop, for some countries representing as much as 30 per cent of their total value of exports, trade returned on a relatively strong path to recovery. A lot of interest has been devoted to pictures similar to Figure 1, which compares the normalised imports of finals and intermediates to the United States. After the Lehman collapse, marked by the red vertical line, intermediates experienced a substantially larger drop in trade compared with final goods. This phenomenon is rather typical for trade during this period. However, a distinction between the intermediates has rarely been drawn. Using the example of two products that could occur within the same supply chain – *Automobile parts and components* a relatively downstream product and *Iron and steel products* a relatively upstream product – Figure 2 shows that some intermediates dropped more than others. Also, the recovery pattern has not been the same across the board.

The change during the crisis happened mostly on the intensive margin. However, as documented by Figure 3, there have also been substantial dynamics on the extensive margin. When looking at the relationships of the United States at the country-HS8 product level, the number of trading relationships had been largely stable from 2005 until the onset of the crisis, with the exception of an obvious seasonal pattern. In the last quarter of 2008, the number of traded relationships suddenly fell dramatically. As shown in the right panel of the figure, the absolute majority of the dropouts happened shortly after the Lehman collapse and by the end of 2010, the number of trading relationships almost fully recovered to its previous level. As Figure 4 shows, the rate of resurrections was very high and the death spans relatively short. The trading resumed just one to three months after its interruption, and only about 10 per cent of the relationships did not resurrect before the end of 2010.

This paper claims that much of the described dynamics can be explained by what the business literature calls the bullwhip effect. This effect is characterised by a magnification of the demand variability for the most downstream product along the chain, with the most upstream producers facing the highest volatility. Bullwhip was first described by Forrester (1961) who showed several examples of it. He attributed his observations to the constant change in organisational behaviour. The actual term has entered the literature more recently through the work of Lee et al. (1997), who spell out four causes of the bullwhip effect: demand forecasting, order batching, price fluctuations, and rationing and shortage gaming. In context of the 2008-09 trade collapse, the demand forecasting mechanism becomes particularly relevant. With the huge demand shock that occurred after Lehman, firms found themselves in a large uncertainty, which complicated formulating the predictions of future demand. In the logic of the bullwhip effect, one would expect that most downstream firms would attempt to run down their inventories to a new desired level, thus reducing their orders to their suppliers. Due to the fact that the inventories are used to meet at least part of the demand, this reduction would be disproportionate compared with the drop in sales of the final product. The suppliers who now find themselves observing a much lower demand for their goods also adjust their inventories and propagate the shock upstream to their suppliers, again in a magnified manner. After the final demand recovers, all supply chain participants not only produce to meet the new demand, but also to replenish their inventories, and the same type of mechanism unravels in the opposite direction. The obvious implication of this effect is that not all intermediates are created equal, and the more upstream producers might experience a much higher volatility than the downstream ones. In extreme cases, this effect might even lead to an interruption of trading relationships.

This paper builds on the insights from the bullwhip effect and shows that the presented stylised facts are consistent with this supply chain phenomenon. First, in a simple framework, I show that after the final industry faces a major demand shock, the volatility of sales, production, and inventories faced by the producers increases with the upstreamness of their product. This volatility is further magnified by a large initial inventories to sales ratio. Second, I show that with a diversified final demand, this effect can become non-monotonic, that is, the volatility of the downstream producers can turn out higher than that of their upstream counterparts. Third, I show empirically, using high-frequency disaggregated US imports data, that this effect has indeed been in place post-Lehman. Fourth, in line with the predictions of the framework, I show that the bullwhip effect can lead to a temporary loss of trading which, in the majority of cases, resumes once the repercussions of the initial shock subside. Lastly, I show that while the origin of trade does not matter, products that have been traded longer and whose market share was larger pre-crisis turned out more resistant to the bullwhip effect.

The paper is structured as follows: Section 2 provides an overview of related literature. Section 3 derives a simple framework of the bullwhip effect and demonstrates, through simulations, how a downstream demand shock will propagate along the chain. Section 4 outlines the sources of data, basic descriptives of the data, and construction of main variables. Section 5 presents the methodology, results, and robustness checks. Section 6 discusses the limitations, possible extensions, and concludes the argument.

2 Literature overview

This paper contributes to two major strands of literature. First, it expands the literature analysing the trade collapse by providing an explanation of not only why the intermediates drop during the trade collapse was disproportionately larger, but also why some intermediates were more adversely affected than others. Second, the insights from the bullwhip effect provide an additional mechanism, not yet explored in the literature, that can generate zero trade flows in the bilateral matrix of world trade.

The ”sudden, severe and synchronized” trade collapse of late 2008 and early 2009 has attracted considerable attention from the research community.[1] The current consensus seems to be that most of the drop, as well as the overreaction of trade to GDP, can be explained by an unusually large demand shock, coupled with a strong compositional effect. After Lehman Brothers filed for bankruptcy in September 2008, a wave of extreme uncertainty spread across the world. The result was a general delaying in the purchases of postponables, such as durables and capital goods, shown, for example by Bricongne et al.(2010). In addition to being most affected, these two categories are also disproportionately larger components of trade than GDP. Bricongne et al.(2010) and Chor and Manova (2010) also show that the credit crunch accompanying the trade drop in the developed world and the withdrawal of funding from the emerging markets led to a strong adverse effect on financially dependent industries.[2]. However, not all studies agree on this point. Mora and Powers (2009) attribute the drop in trade finance to lack of demand and, similarly, Levchenko et al. (2010) consider finance a secondary factor.

Without much conclusive evidence against the financial channel, and with the majority of the trade flows currently consisting of intermediates, the role international supply chains may have played in the collapse has also received a considerable amount of attention. The focus on this factor is particularly prominent in attempts to explain the overreaction of trade in relation to GDP. However, O'Rourke shows famously, with his Barbie example, that a higher elasticity of trade to GDP can only be explained by vertical integration if marginal trade disproportionately affects vertically disintegrated goods, and not all trade is vertically disintegrated. Benassy-Quere

[1] Baldwin (2009) provides an overview of early studies on the subject
[2] See e.g. Cetorelli and Goldberg (2010)

et al.(2009) confirm this view by showing that existence of supply chains should lead to a proportional drop in trade to GDP. They attribute the observed disconnect to a price effect and short-term factors like lack of finance, inventory adjustment, and change in expectations. Similarly, Escaith et al. (2010) conclude that, even though the emergence of supply chains constituted a structural change in world trade in the 1980s, the trade elasticity only increased in the transitory phase and then returned to long-term equilibrium. Along the same lines, they state that, in this crisis, the increase should only be transitory and mainly attributable to a composition effect, that is that most of the drop has happened in durables, which also tend to be the most vertically disintegrated category of goods. Bems et al. (2010) list potential re-nationalisation of the chains, increased number of transactions between separate stages, and bias of trade towards vertically disintegrated goods as potential triggers that could have helped propagate the initial shock. In contrast to the more pessimistic views, Altomonte and Ottaviano (2009) point out that supply chains could have been a factor of resilience in the crisis, as existing supply chains are difficult and undesirable to sever because of contractual arrangements and high initial sunk costs.

Even though no extensive analysis of the role of the bullwhip effect has been provided, the literature relating to the collapse has not completely ignored this phenomenon. Alessandria et al.(2010; 2011) despite never mentioning the word ”bullwhip”, work with this exact type of intuition. In their analysis, they use the example of the car industry to show that during the crisis, as sales of cars dropped dramatically, sellers found themselves with an undesirable stock of inventories. Consequently, they started running down these inventories as the demand was dropping. This action led to a lack of orders to their suppliers and a much larger drop in sales of parts and components in comparison with sales. However, these authors focus on explaining the role of the inventory adjustment for magnifying the trade elasticity during the crisis; they do not study a further propagation of the shock to more upstream producers. Two other papers mention the bullwhip effect specifically. Altomonte et al.(2012) note that intermediate exports of French firms experienced a relatively larger drop than those of other firms and attribute this result to the bullwhip effect. Further, they point out that the drop may be reduced for transactions involved in intra-firm rather than arm’s-length trade. To support this finding, they cite the fact that a firm will have a better ability to coordinate the inventories of a chain internally. Escaith et al.(2010) mention the bullwhip effect, alongside the composition effect, as one factor explaining the increased short-term trade elasticity. They do not, however, provide a formal test of it.

In addition to a higher upstream volatility, the bullwhip effect predicts that an upstream product faces a higher probability to temporarily lose sales after a major adjustment in demand. This development results in a zero trade flow. Zeros in trade are extremely common[3]. and the reasons for their occurrence have been extensively studied. Yet, none of the previous studies have provided a supply chains-related explanation. There are several explanations solely based on theory. According to Haveman and Hummels (2004) the predominance of zeros in the SITC4 level, bilateral trade data would be consistent with a model of incomplete specialisation. In Eaton and Kortum's (2002) model, transportation costs are driving wedges between relative production efficiencies of the countries, thus generating zero flows to some destinations. Another class of models started by Melitz (2003), predict that only the most productive firms will export. Baldwin and Harrigan (2011) assess the latter two models, as well as the monopolistic model of Helpman and Krugman (1987), and find that, while the Melitz model performs best in explaining the US trade patterns, it fails to account for the observed spatial patterns. They provide an extension of this model that accounts for this limitation.

The empirical literature looking at the dynamics of the extensive margin has expanded relatively recently, starting with the works of Besedes and Prusa(2006a; 2006b). They show that most trading relationships last for a very short period of time – just two to four years – and that differentiated products have a longer trade duration. They also infer that the initial size of trade matters for survival. Bernard et al.(2009) show that most exporters start small and, in the short-term, the contribution of the extensive margin is very low. Over a 10 year span, however, they contribute more than half of the growth in trade. They also show that variations in imports and exports across trading partners are primarily due to extensive margin, while variation in trade across one year intervals are dominated by intensive margin. This observation supports the view that most of the adjustment in the Great Trade Collapse happened on the intensive margin[4]. In a paper closely related to this study, Beverelli et al.(2009) show that more experienced exporters in less financially dependent sectors had a better chance to continue exporting during a banking crisis,

[3]Depending on product definition there are as many as 70 to 90 per cent of zeros in the bilateral trade matrix. See for example Dias (2008) or Baldwin and Harrigan (2011)

[4]Bricongne et al. (2010) show that this has been the case for France, Schott (2009) shows evidence for the United States, and Wakasugi (2009) devise the same conclusion using Japanese data

but they do not look into the importance of additional product characteristics.

3 The bullwhip effect

3.1 The simple algebra of bullwhip

This section demonstrates the mechanics of the bullwhip effect and shows that it occurs when firms hold inventories. I assume that before each final product is completed, the production goes through n stages. I further assume that each stage of production is located in a different country. The production process starts with a primary product sold by the stage n supplier to the producer at stage $n-1$, who processes it and, subsequently, sells it to be used in the production of the supplier at stage $n-2$. Then, the completed intermediate is further processed and, after passing through the entire sequence of n stages, the final product is eventually sold to the consumer. I will be referring to the finals producer as stage 0, the first level supplier as stage 1, and the most upstream producer as stage n.

The finals producer faces a demand D_t^0 and sets inventories based on a simple rule:

$$I_t^0 = \alpha D_t^0 \tag{1}$$

Therefore, the inventories are set as a share α of the demand. The producer makes decisions based on the purchases of intermediates from the first stage supplier. These will be defined as the sum of the realised demand for the final goods and the inventory adjustment:

$$P_t^0 = D_t^0 + I_t^0 - I_{t-1}^0 \tag{2}$$

The purchases of the finals producer are simultaneously equal to the demand of the stage 0 producer for the intermediates produced by the first stage supplier, which I denote as D_t^1. We can express this first stage demand as a function of the demand for final goods:

$$D_t^1 = (1+\alpha)D_t^0 - \alpha D_{t-1}^0 \tag{3}$$

Just like the finals producer, the first stage producer holds a share α of its demand in inventories. The production is again driven by the demand and by the desired inventory adjustment. After simple manipulations, I can express the demand for stage 2 as a function of the demand for finals as follows:

$$D_t^2 = (1+\alpha)^2 D_t^0 - 2\alpha(1+\alpha)D_{t-1}^0 + \alpha^2 D_{t-2}^0 \tag{4}$$

This, again, is the same as P_t^1, that is, the purchases of stage 1 from the 2nd stage producer. Continuing with the same simple logic, we can write the demand of stage n as a function of the demand for final products:

$$D_t^n = (1+\alpha)^n D_t^0 - n\alpha(1+\alpha)^{n-1} D_{t-1}^0 + ... + (-1)^n \alpha^n D_{t-n}^0 \tag{5}$$

It can be further shown that, after the producer of final products faces a demand shock, the sales of each stage will be magnified by a factor $(1+\alpha)$, that is:

$$\partial D_t^n / \partial D_t^0 = (1+\alpha)^n \tag{6}$$

This result implies that the only way to avoid magnifying the transmission of the demand shock along the chain, is not to hold any inventories at all. If a firm decides to hold inventories, the impact on sales rises the further upstream the firm is on the production chain. The impact is also magnified when the number of inventories held in relation to sales is greater.

However, there are circumstances under which this effect can become non-monotonic, that is, the volatility at stage $n-1$ can be larger than the volatility at stage n. This may happen when a somewhat upstream supplier is involved in additional chains, while the more downstream product is specialised and sold to just one or a limited number of industries. One could reasonably expect that the closer a supplier is to the final producer , the more specialised the supplied intermediate will be, and the less likely it will be that she will be able to supply for other chains, too. To use an example from the car industry, an upstream producer of steel will supply not only for the automobile industry, but also for a range of other industries, such as machinery or construction. On the other hand, a downstream producer of car seats can only sell its products to the car industry. Therefore, when a demand shock hits the car industry, the downstream producers will be fully exposed, while the impact can be mitigated for the more upstream industries,. This result, however, will be conditional on the extent to which the shocks to the target final industries are similar. Formally, I can write the total demand for the sales of each stage of production as a sum of demands of all the final industries which use intermediates from this producer, weighted by their importance for the supplier γ_m.

$$D_t^n = \sum_{m=1}^{M} \gamma_m D_t^0(m) \tag{7}$$

The variance of this sum will be the sum of the variances of the demand from all final (stage 0) industries and their covariances.

$$Var(D^n) = \sum_{m=1}^{M} \gamma_m^2 Var(D_m^0) + 2\sum_{i<j} \gamma_i \gamma_j Cov(D_i^0, D_j^0) \tag{8}$$

This expression implies that the volatility of demand a producer is facing can be reduced by supplying for industries that face a different type of shocks, but only if the sum of the covariances works out to be negative.

3.2 Simulations of permanent and temporary demand shocks

In order to better understand the expected dynamics of sales, I simulate responses of the final stage of production and the three stages furthest downstream after the final industry has been hit by a temporary or permanent shock. The nature of the shocks I use is depicted in Figure 5. Both the permanent and temporary shocks are characterised by a 20 per cent drop of sales for the final industry after a demand shock hits in period 2. In the case of the temporary shock, the demand promptly adjusts back to its original level in the following period. In contrast, the permanent shock leads to a persistent drop to the new lower level of demand. Taking into account these different types of shocks and various inventory rules, I simulate the developments of sales and inventories. In the extreme case, when all firms in the supply chain hold no inventories ($\alpha = 0$), their production corresponds to the observed demand and the adjustment is immediate for both types of shocks. Firms observe the demand for their goods, which determines their production and, as there are no inventories, the production simply equals sales. The sales, production, and inventories at all stages of production will, thus, exactly reproduce the pattern of the shocks depicted in Figure 5.

The situation changes dramatically once the firms start holding some inventories. With the replenishment rule of inventories equal to half of the observed demand, that is, $\alpha = 0.5$, the volatility of sales of the first stage producer exceeds that of the finals producer and rises further at stages 2 and 3. The pattern is very similar for both the temporary and permanent shocks. In the case of the temporary shock, however, the volatility is larger. The reason for this contrast is that, after responding to the initial negative shock by running down their inventories in the second period, the producers are faced with a much higher demand in the next period. Therefore, in this period, their suppliers are not only producing to meet the higher demand, but also to replenish the inventories to the new desired level. To understand this logic numerically, let us suppose the final producer sells a value of 100 in the first period and he buys 100 from the first stage supplier who, in turn, buys 100 from the second stage supplier. Let us also assume that they all keep their inventories at 50. In the next period, when the demand shock hits, the finals producer can only sell 80. With the new level of demand, she only needs to keep 40 in inventories. Therefore, her order to the first stage supplier in this period will be 70. With this demand, the first stage supplier now only needs to keep 35 in inventories, so she only orders 55 from the second stage supplier. In the next period, when the demand goes back up to 100, the final producer finds herself with fewer inventories than she would like to have and, therefore, orders 110 from the first stage. The first stage producer now wants to have 55 in inventories, so she orders 130 from the second stage. The behaviour of inventories reflecting these decisions is depicted in Figure 7.

The effects stay qualitatively the same when the inventory holdings increase further to $\alpha = 1$. However, as Figure 8 demonstrates, the volatility of sales gets substantially magnified. Now, there can even be periods when the producers at stage 3 do not produce or sell at all. The corresponding inventories behaviour is shown in Figure 9. While things are mostly the same as before for the permanent shock, the picture gets more dramatic for the most upstream producers when the final industry faces a temporary shock. Not only do they completely lose business in the second period, in the third period, when the final demand has already recovered, they are suddenly facing a much larger demand. They must respond to this demand while also replenishing their inventories. In the next period, when they realise the rise in demand was short-lived, they are stuck with high inventories, as the downstream producers do not buy, but simply run down their own stocks of inventories instead. Over time both the inventories and sales for all stages get back to normal. However, the adjustment time increases with the upstreamness of the product.

3.3 Limitations

Obviously, the manner in which the model and simulations have been presented so far is very simplistic. In reality, firms will use more complex techniques to forecast demand and will not be able to easily and immediately adjust their production and inventories. To be efficient, most firms operate close to their production capacity and have limited storage capacity for the inventories. Holding inventories has a high opportunity cost and if perishability is a concern or storing limitations apply, they might lead to additional losses. However, despite the strength of the assumptions, the fundamental logic of the argument does not change when implementing a more sophisticated demand-forecasting rule and imposing a cap on production and inventories. In a more realistic setting, in which production and inventories cannot be freely adjusted to any value and firms will use more than just last period demand to predict their sales, the observed volatility will not be as extreme. Nonetheless, the results will stay qualitatively the same. As long as the expected demand and inventories are related to some extent, the volatility will still increase with each stage and there can still be periods in which a supplier is neither producing nor selling – even though, arguably, the magnitude of the shock would then need to be larger. The extent to which volatility will rise will depend on the size of the shock, the extent of inventory holdings, and the concentration and nature of final demand.

3.4 Testable hypotheses

The above model and simulations have shown that when firms hold inventories, the further upstream a supplier is located, the more volatility she will face and the observed volatility rises as the inventory holding of the chain increases. Under extreme circumstances, the very upstream producers might also completely lose business, while holding amounts of inventories that are not desirable. The volatility implications, however, can be mitigated when the final demand is diversified, that is, the producer supplies for a range of chains with uncorrelated or negatively correlated demands. Therefore, whether we will observe the bullwhip effect after a major demand shock will be purely an empirical matter. The preliminary evidence presented suggests that the bullwhip effect might indeed have played a role after the unexpected demand collapse post Lehman bankruptcy. A more formal analysis in the subsequent sections is based on testing the following predictions implied by the framework:

- *first,* after a demand shock, the volatility of production and sales will be increasing with the stage of production.
- *second,* high inventory-to-sales ratios and lack of diversification in final demand exacerbate the sales volatility magnification of upstream production stages.
- *third,* a demand shock affecting the sales of final goods can lead to a *temporary* complete loss of sales of upstream producers.

4 Data

4.1 Trade data

In order to test the hypotheses outlined in the previous section, I will need high frequency disaggregated trade data, which will be used as a proxy for sales. The trade data are taken from the USITC that publishes monthly bilateral data for the United States, classified at a very detailed Harmonized System (HS) eight-digit nomenclature. I am using a sample ranging from January 2005 to December 2010, which allows me to cover a sufficiently lengthy pre-crisis window, as well as the whole trade collapse and recovery period. The analysis covers about 95 per cent of total US imports, which is supplied by close to 50 of the most important exporters. The countries included in the sample, their share in imports of the United States, and the number of products they exported to the United States in 2006, that is, pre-crisis, are summarised in Table 1. Unsurprisingly, the imports are dominated by China, the NAFTA trading partners Canada and Mexico, and the export superpowers Germany and Japan. These five countries already account for more than half of the total imports of the United States. The exports from this group are also very diversified, with each selling close to or more than 6,000 different products. A diversification this high is characteristic also for all other imports from advanced countries, such as the United Kingdom or Italy, even though their share in total imports is relatively lower. The remaining countries included in the sample are much less important from the perspective of the United States, both in terms of total values sold, as well as the numbers of varieties provided. In a stark contrast to the thousands of products exported to the United States by the most important trading partners, there are only a handful of products sold by Algeria, Angola, Kuwait, or Saudi Arabia, which serve mostly as commodity providers for the United States.

4.2 The technological measures

The second component needed to test the bullwhip effect are proxies for the three technological measures that, based on the theory, contribute to its occurrence: the upstreamness of a product, the concentration of final demand, and the inventories to sales ratio. These measures are computed at the input output (IO) six-digit level used by BEA. This classification is closely related to the US industrial classification NAICS. In order to match these measures with the trade data, I am using the concordance between HS and NAICS provided by BEA. The descriptives of the three measures and the correlations between them are captured in Table 3 and some sample products are listed in Table 2.

4.2.1 The upstreamness

To measure upstreamness, I use a proxy based on the input output table of the United States, taken from Antras et al. (2012). They define the upstreamness of industry i implicitly as:

$$U_i = 1 + \sum_{j=1}^{N} \delta_{ij} U_j \tag{9}$$

where δ_{ij} corresponds to:

$$\delta_{ij} = \frac{d_{ij} Y_j}{Y_i - X_i + M_i} \tag{10}$$

Y_j refers to the total output of industry j and d_{ij} is the dollar amount of sector's i output needed to produce a dollar of sector's j output. The remaining terms, X_i and M_i, refer to exports and imports respectively. As the input output table does not differentiate between the use of foreign and domestic inputs, the adjustment for net trade is needed to correctly represent the total upstreamness of an industry in an open economy which would be otherwise biased.[5] Using matrix algebra, equation (9) can be solved for all industries as:

$$U = [I - \Delta]^{-1} \mathbf{1} \tag{11}$$

where the ij component of Δ corresponds to δ_{ij} and $\mathbf{1}$ is a column vector of ones.

The computation of the upstreamness measure is based on 425 industries and it takes values between one, for the final products, to 4.65, for the most upstream product, which is the petro-

[5] For demonstration of how this bias arises see Antras et al. (2012).

chemical manufacturing industry. Table 2 provides additional examples of industries in between these two extremes. [6]

4.2.2 The index of demand concentration

As the upstreamness alone is not enough to observe a bullwhip-style magnification of a demand shock along the chain, I also need to control for the diversification of demand – which I will rather define as the inverse, that is, the demand concentration. The computation of this proxy is also based on the US input output table and is constructed in two steps: First, I compute the production shares s_{ij} industry i contributes to industry j relative to total production of industry i. Second, I use these shares to construct a normalised Hirschman Herfindahl concentration index that can be expressed for each industry i as follows:

$$C_i = \frac{\sum_{i=1}^{N} s_{ij}^2 - 1/N}{1 - 1/N} \tag{12}$$

The measure varies between zero and one, with one being the highest concentration, implying that all production is targeted at one industry. The measure also takes a value of one for all final products. As shown in Table 3 in the sample, the values of the measure cover the full range between zero and one with an average value of 0.58. The same table also documents that the index is highly negatively correlated with the upstreamness measure. This is not very surprising, as more upstream products tend to be less specialised. An obvious limitation of this measure is that, in relation to the theory, it fails to capture the correlations of final demand. Unfortunately, given the data limitations, a more representative proxy is not easily available.

[6] To understand further how this measure arises, it is useful to realise that most manufacturing industries use a relatively large number of suppliers, many of which contribute only a very small share of the total value added. The absolute majority of the value added is contributed on the first one or two stages of production. Number of suppliers tends to increase at each stage, while the contributions to the value added of the final product are dropping. For example, in the car industry, looking at the first three stages of production, more than half of the suppliers are located at stage three. They, however, provide less than a 10 per cent contribution to the overall value added of the industry.

4.2.3 Inventories to sales

The final component needed to test the bullwhip hypothesis is a reasonable approximation of the ranking of inventories to sales ratio across industries. I will be referring to this measure simply as Alpha. To construct this proxy, I use the NBER-CES manufacturing industry database, which provides detailed information about the inventories and values of shipments of all US NAICS6 manufacturing industries for the period 1958-2005. The disadvantage of these data is that they are only available for manufacturing industries. Even though upstreamness and concentration can also be computed for commodities, we will lose these products when including all three measures in the analysis. The total number of IO industries in the sample will drop from 425 to 279.

Figure 10 provides a snapshot of this rich dataset documenting that there has been a steady decline in the inventories-to-sales ratio across all industries over time. This decline is consistent with the existing literature and attributable to technological progress that led to better inventory management in the more recent periods. It is important for this study that this is an overall trend rather than something driven by a handful of industries, as changes in rankings could invalidate the results. However, it seems the rankings have persisted over time. Table 4 shows that the correlations between measures computed for different decades are very high and significant. In addition, this table also shows that the measure is not sensitive to the way of aggregation over time, as the average and median computed for each industry over the whole sample period are very highly correlated. This implies that the choice of alpha should not substantially affect the results. Therefore, I will be using just the measure computed for the most recent decade in the main results section and keep the rest for robustness tests.

Column 3 of Table 3 shows values of the inventories-to-sales ratio for sample NAICS industries. The measure ranges from 0.02, for the light truck and utility vehicle manufacturing industry, to 0.52, for aircraft manufacturing. Compared with the values used in the simulation, this mean of 0.14 is relatively low. The correlation of alpha with both concentration and upstreamness is relatively low and, in contrast to the study by Altomonte et al. (2012), the negative sign does not seem to suggest that the inventories increase with upstreamness.

5 Empirical analysis

The empirical analysis proceeds in three steps: First, I test the prediction that upstream sales volatility exceeds the downstream volatility. I use the Glejser heteroscedasticity test and control for inventories to sales and concentration. Second, I look at whether or not bullwhip generates zero trade flows, if the zeros are persistent, and if there are factors that can mitigate the impact of the effect. Finally, I perform a battery of robustness checks of the econometric methods and the level of data aggregation.

5.1 Do upstream producers face a higher volatility?

To test the prediction that sales volatility of upstream producers exceeds the volatility of downstream producers, I employ a version of the Glejser heteroscedasticity test. This test relies on comparing the residual trade, that is, the part that cannot be explained by time and product characteristics, before and after the Lehman shock. The estimation is done in two stages: First, I estimate an equation explaining the levels of trade for each of the HS8 products imported to the United States during the 2005-10 period. Second, I take the absolute values of the residuals from the first stage and look at whether upstreamness, inventories-to-sales ratio, and demand concentration have power for explaining the unusually large residuals that occurred after the Lehman collapse. I aggregate the data to product level and disregard the country dimension for two reasons. First, the behaviour of the sales should not depend on the origin of the good, but only on its characteristics. Even though, in practice, some exporters are probably better able to defend their market shares than others, this is not important for proving the volatility prediction. Instead, I will further address this issue in the robustness section. Second, the incidence of zero flows is much smaller at this aggregation level and, thus, the issues their existence would introduce for the log specification are minimised. Specifically, in the first stage I estimate:

$$LNIMP_{it} = \delta_i + \delta_t + u_{it} \tag{13}$$

where $LNIMP_{it}$ is the (log of) imports to the United States from industry i in time t, the set of fixed effects δ_i controls for unobserved industry characteristics while δ_t captures time characteristics such as the strength of demand or aggregate seasonality. This specification provides a prediction for how much of each product should be imported to the United States at any given timepoint, given the inherent characteristics of the product and prevailing demand conditions. Next, I use the absolute value of the residuals from the first stage as the dependent variable in the second stage, specified as follows:

$$|\hat{u}_{it}| = (\beta_1 Upstreamness_i + \beta_2 Concentration_i + \beta_3 Alpha_i) * Crisis_t + \delta_i + \delta_t + \varepsilon_{it} \tag{14}$$

The *Crisis* variable is defined in terms of a crisis window starting in September 2008, which was the date that marked the Lehman bankruptcy as well as the beginning of the worldwide decline in international trade. It is not entirely clear how to define the length of the crisis window ex-ante and I will be experimenting with several definitions. If the bullwhip hypothesis is correct, each of the technological measures is expected to increase volatility and, thus, all three interactions with crisis shall turn out positive. I am also including the time and product effects, to account for deviations specific to the product or to the timepoint. I do so because some products might be inherently more volatile and the general trade volatility might have been changing over time. Given that the technological measures are computed at the NAICS level and the trade data are at HS8 level throughout the estimations, the errors are clustered at the industry level.

The results of the second stage of the estimation are summarised in Table 5. Each column of the table refers to a different crisis window. The first window is defined as the period from September 2008 to April 2009, that is, from the point when trade started declining to the first signs of recovery. The second period is cut off at the end of 2009, the third ends in mid-2010, and the last, at the end of 2010. In line with the expectations, the signs of the estimated coefficients on all three interaction terms are positive. However, only upstreamness and inventories-to-sales are significant. Also, as one would expect, the explanatory power of upstreamness declines as the crisis window increases. There are several potential explanations for the consistent insignificance of the estimated coefficient associated with the concentration measure. This result could be attributable to the relatively high correlation between this measure and the measure of upstreamness. Alternatively, high concentration might also be a proxy for high specialisation. This fact is relevant because it is possible that the buyers would prefer to continue buying from their most important suppliers in order to avoid the potential cost of looking for new suppliers once the crisis subsides. This action would, thus, reduce the impact on volatility. More specialised products also have the potential to be more highly integrated, which could reduce the information distortion about the final demand, leading to a lower impact on volatility from concentration. Finally, by not taking the correlation of final demand into account, this measure is only an imperfect approximation of the measure suggested by theory. There is a possibility that products with a very concentrated final demand are supplied for industries facing uncorrelated or negatively correlated demands, again reducing the observed volatility.

The first stage, as proposed in Equation (13), controls for overall seasonality of US imports. If product specific seasonality differs widely across products, however, the equation might not capture this change very well. Table 6 reports the results of two robustness tests of the Glejser specification that take this issue into account. The first test amends the first stage of the estimation, using the year-on-year change of exports, rather than their levels as the dependent variable. The second robustness test is a one-stage estimation that uses Hodrick-Prescott filtered imports of each product as the dependent variable. Both tests provide results that are very similar to the original estimation. The robustness tests are shown for the shortest and longest crisis window only. The results for the unreported crisis windows, however, are consistent with those reported in Table 5.

5.2 Are more upstream producers more likely to go out of business?

Another prediction of the bullwhip effect is that products with high values of their technological measures are more likely to drop out of business following a demand shock. To test this hypothesis, I estimate the following probability model:

$$P(dropout)_{ci} = X_{ci} + \eta_1 Upstreamness_i + \eta_2 Alpha_i + \eta_3 Conc_i + \delta_c + \varepsilon_{ci} \tag{15}$$

The dataset is now constructed at the country and HS8 product level. The inclusion of country level here substantially increases the occurence of zero flows. In order to control for country characteristics, such as level of tariffs, geographical closeness, or importance of the trading partner for the United States, I am enclosing a set of country dummies δ_c. This implies that the effects will have a within-country interpretation. In short, I will be comparing how the technological measures affect the probability of different types of products to drop out within the same country. The dependent variable – the probability to drop out – is equal to one if the imports of product i from country c turned from non-zero to zero during the post-Lehman trade collapse period September 2008 to April 2009. The selection of this period is driven by the fact that after April, trade overall started increasing and therefore the drops after this period would no longer be directly attributable to the post-Lehman demand shock[7].

The vector of controls X_{ci} contains the measure of *Experience* for each country-product, which is computed as the number of months product i has been traded between country c and the United States three years prior to the Lehman collapse. Therefore, this measure can be interpreted as the intensity of recent experience. The prior is that the higher this experience, the lower the probability the product will not be traded after this period. In addition, given that important products are less likely to drop out, following Beverelli et al. (2009), the vector X_{ci} also includes the variable *Market share*, which is constructed as a ratio of US imports of product i from country c and the average imports of product i to the United States from all trading partners.

Table 7 shows the result of the estimation. Columns 1 and 2 contain the estimates of a linear probability model and probit estimates are reported in columns 3 and 4. Since I included country dummies, the probit estimation could potentially suffer from the incidental parameter problem. However, given the large size of the dataset and a much larger number of products in comparison with countries, the estimates are actually very similar. It seems that in this particular setting, the two methods can be used interchangeably. Column 5 shows that even excluding the dummies completely has little bearing on the estimates. As the errors could be potentially correlated both within countries and within products, I am clustering the standard errors of the linear probability model by industry in column 1, by country in column 2 and by country and industry in column 3.

As documented by Table 7 all three technological measures turn out positive and significant throughout the estimations, implying that all of them are strong predictors of the probability of a

[7]Nevertheless, the results remain robust to different definitions of this window – both shorter and longer

trading relationship to be interrupted. Moving one stage upstream in the supply chain implies an increase in probability to drop out post-Lehman by 1.4 percentage points. The exact same rise in probability to drop out occurs when the concentration index of a product rises by 0.5, let us say from 0.25 to 0.75. Finally, raising the inventories-to-sales ratio by 0.1 increases the probability of no trade by 2 per cent. A trading relationship that happens very high upstream and in a supply chain with a high inventory-to-sales ratio, however, can improve its chances of survival if it has been around for long enough and if its importance was large enough. An additional 12 months of experience improve the probability of a product being traded continuously by 6 per cent, and increasing the share of trade by just one percentage point improves the odds for a product to stay in business by 8 per cent.

5.3 Which drop outs reappear?

The dynamics of the bullwhip effect documented in Section 3 imply that while drop outs from trading are possible, even the products furthest upstream should return back to trading after the repercussions of the initial demand shock subside. Even so, depending on the nature of the shock, the length of the death span of a relationship might be longer for an upstream product. As already outlined in the introduction, most trading relationships that disappeared post-Lehman were recovered very soon after they dropped to zero. In the subsample of the products used in the estimation, the probability to resurrect is almost 90 per cent. The death spans of products that recover before the end of 2010 also tend to be rather short, with the mean at 4.5 months and with some 30 per cent of relationships already recovering after one month of no trading.

This section looks at the probability of a product reappearing before the end of 2010, after it has dropped out during the global trade collapse period. It also examines the determinants for returning back to trading. I estimate the following specification:

$$P(resurrection)_{ci} = X_{ci} + \eta_1 Upstreamness_i + \eta_2 Alpha_i + \eta_3 Conc_i + \delta_c + \varepsilon_{ci} \qquad (16)$$

The dependent variable takes a value of one if a trading relationship reappeared before the end of 2010, after being interrupted in the period September 2008 to April 2009. I am using the same set of controls as in Equation 15.

The results in Table 8 summarise whether or not the technological variables behind the bullwhip effect can help explain why 10 per cent of trading relationships do not resume trading more than two years after the crisis. Columns 1 and 2 show the results from linear probability models, with errors clustered at the industry and two-way country-industry level respectively. Column 3 shows the results of a probit estimation. The results throughout these three estimations are, again, very similar. Of the three technological measures, only upstreamness is a significant predictor of a resurrection of a trading relationship. Namely, a producer located at stage 3 of production will have a 0.8 percentage point lower probability of recovering the trading relationship than a stage 2 producer. Previous experience also matters. Compared with a product that has been traded for 12 months, a product which has been traded for three years before the crisis has a 1.8 percentage points higher probability to get back to trading after it has dropped out. Somewhat surprisingly, the importance of the product pre-crisis, as captured by the *Market share* variable, enters with a negative sign, that is higher share reduces the probability to resurrect.

5.4 Does the origin of trade matter?

In order to increase the incidence of zeroes for the estimations, I have so far studied the extensive margin dynamics at the country-product level. However, in theory, for bullwhip to occur, the origin of the product should not matter; only its technological characteristics should. The purpose of this section is to assess whether this prediction really holds in practice or if some exporters are better able to protect their market shares. For instance, long-established trading partners or firms with superior marketing strategies could potentially fare better in the crisis. Also, as documented by previous literature, one could potentially expect more developed countries to be better able to push their products and crowd out similar inputs from less developed countries.[8]. Tables 9 and 10 show the results of estimation of Equation 15, including an interaction of the upstreamness measure with different country characteristics. I look at the effect of contiguity, common language, distance, GDP per capita, and the effect of having signed an RTA with the US. All variables are taken from the dataset constructed by Head et al. (2010). Overall, country

[8]See, for example Molina and Fugazza (2009) or Brenton et al. (2010)

characteristics do not seem to matter much in alleviating the effect of upstreamness – for either the drop out or the resurrection. The only variable that turns out marginally significant in the case of drop out is common language, which can reduce the impact of upstreamness by 0.8 percentage points. In case of resurrection, upstream products traded with countries sharing a common border, in this case Mexico or Canada, have a higher probability to resurrect than their more remote counterparts.

5.5 Can experience or size mitigate the impact of the bullwhip effect?

The results so far have confirmed the observations from the previous literature stating that products that have been traded for longer and in larger quantities have a higher probability to survive. An open question is whether these characteristics can help mitigate the impact of the bullwhip effect, that is, whether highly experienced or large products have a higher probability to survive or go back to trading. To test this hypothesis, I estimate the baseline specifications for drop out and resurrection on the top and bottom quartile products, split by experience or market share. As shown in Table 11, there is a considerable difference between the response of highly experienced products and that of products with less experience. The upstreamness is a significant positive predictor of drop out and negative of resurrection only for product with short pre-crisis trading experience. Table 12 shows that, when it comes to drop outs, upstreamness of a product matters equally for products with small and large pre-crisis importance. However, only relatively small products are unlikely to return to trading due to their upstreamness.

5.6 Does aggregation matter?

The final concern is if the results are robust to different levels of aggregation. The entire analysis so far has been done at the HS8 level. Given the monthly frequency, this level might be a too high a disaggregation as it is quite likely that not every country trades its products every month. An additional concern is that not all flows may be registered in the correct month. Table 13 shows the drop out probability estimations done at HS6 and HS4 levels. For comparison, the first column also includes the original regression. The upstreamness coefficient stays consistently positive and significant, the results on alpha and concentration, however, grow somewhat weaker. This leads to the conclusion that from the three technological measures driving the bullwhip effect only upstreamness is strongly robust.

6 Conclusions

This paper shows that part of the US imports dynamics observed during the Great Trade Collapse can be explained by what the business literature calls the bullwhip effect. The effect contributes to explaining the causes of the collapse on both the intensive and the extensive margin.

Using a simple framework, I demonstrate that after final goods suffer a demand shock, upstream suppliers face a greater volatility of sales than their downstream counterparts and might even lose sales temporarily. The effect, which is driven by inventory adjustments, gets magnified when the inventory-to-sales ratio of the industry is high. The volatility of a downstream production stage might exceed the volatility of its suppliers if the upstream producers operate in networks of chains with uncorrelated demands. The analysis is limited by a somewhat simplistic inventory rule. However, as long as the inventory management of firms is at least partially related to expected demand, as the inventory management literature suggests, the main predictions will not change.

The hypotheses derived from the framework are tested using US industry-level import data. Using a Glejser heteroscedasticity test I show that the volatility of trade after the Lehman shock is higher for upstream industries. These are also more likely to drop out of trading completely. Most of the drop outs, however, are temporary and about 90 per cent of products return to trading within two years after the shock. The products that do not return are more likely to have been traded for a shorter period and in smaller quantities pre-crisis. Bullwhip-driven drop outs and recoveries are propelled mostly by product characteristics; country characteristics do not seem to have much effect in mitigating the impact. The results are robust to different econometric methods and data aggregations.

These results provide some interesting policy insights. First, they offer a possible explanation of why some countries' trade might be more volatile than that of others. They also establish a mechanism of international transmission of shocks. Second, they suggest that under some circumstances, zero trade flows might occur in a subset of industries as a natural consequence of the production structure in which they operate and do not necessarily require a policy response. Some attention should be given to small and inexperienced exporters which seem more vulnerable during major demand shocks.

A possible avenue for further research would be examining whether or not the bullwhip effect has any consequences for commodity prices. Commodities, being at the very upstream stages of production, should be most affected by major demand shocks. Unlike downstream products, however, their prices respond much faster to changes in demand, which might also result in a stronger response by prices than quantities. This reaction might have some explanatory power towards why the commodity prices plummeted at the time of the Great Trade Collapse.

References

G. Alessandria, J. P. Kaboski, and V. Midrigan (2010), “The great trade collapse of 2008-09: An inventory adjustment?”, NBER Working Papers 16059, National Bureau of Economic Research, Inc.

G. Alessandria, J. P. Kaboski, and V. Midrigan (2011), “US trade and inventory dynamics”, *American Economic Review*, *101*(3), 303–07.

C. Altomonte, F. D. Mauro, G. Ottaviano, A. Rungi, and V. Vicard (2012), “Global value chains during the great trade collapse: a bullwhip effect?”, Working Paper Series 1412, European Central Bank.

C. Altomonte and G. Ottaviano (2009), *The Great Trade Collapse: Causes, Consequences and Prospects.*, VOX.

P. Antras, D. Chor, T. Fally, and R. Hillberry (2012), “Measuring the upstreamness of production and trade flows”, NBER Working Paper 17819, National Bureau of Economic Research.

R. Baldwin (2009), *The Great Trade Collapse: Causes, Consequences and Prospects.*, VOX.

R. Baldwin and J. Harrigan (2011), “Zeros, quality, and space: Trade theory and trade evidence”, *American Economic Journal: Microeconomics*, *3*(2), 60–88.

R. Bems, R. C. Johnson, and K.-M. Yi (2010), “Demand spillovers and the collapse of trade in the global recession”, *IMF Economic Review*, *58*(2), 295–326.

A. Benassy-Quere, Y. Decreux, L. Fontagne, and D. Khoudour-Casteras (2009), “Economic crisis and global supply chains”, Working Papers 2009-15, CEPII research center.

A. B. Bernard, J. B. Jensen, S. J. Redding, and P. K. Schott (2009), “The margins of US trade”, *American Economic Review*, *99*(2), 487–93.

T. Besedes and T. Prusa (2006a), “Ins, outs, and the duration of trade”, *Canadian Journal of Economics*, *39*(1), 266–295.

T. Besedes and T. J. Prusa (2006b), “Product differentiation and duration of US import trade”, *Journal of International Economics*, *70*(2), 339–358.

C. Beverelli, M. Kukenova, and N. Rocha (2009), "Are you experienced? Survival and recovery of trade relations after banking crises", Staff Working Paper ERSD-2011-03, WTO.

P. Brenton, C. Saborowski, and E. von Uexkull (2010), "What explains the low survival rate of developing country export flows?", *World Bank Economic Review*, *24*(3), 474–499.

J.-C. Bricongne, L. Fontagne, G. Gaulier, D. Taglioni, and V. Vicard (2010), "Firms and the global crisis: French exports in the turmoil", Working Paper Series 1245, European Central Bank.

N. Cetorelli and L. S. Goldberg (2010), "Globalized banks: lending to emerging markets in the crisis", Staff Reports 377, Federal Reserve Bank of New York.

D. Chor and K. Manova (2010), "Off the cliff and back? Credit conditions and international trade during the global financial crisiss", NBER Working Papers 16174, National Bureau of Economic Research, Inc.

J. Eaton and S. Kortum (2002), "Technology, geography, and trade", *Econometrica*, *70*(5), 1741–1779.

H. Escaith, N. Lindenberg, and S. Miroudot (2010), "International supply chains and trade elasticity in times of global crisis", MPRA Paper 20478, University Library of Munich, Germany.

J. Forrester (1961), *Industrial Dynamics*, Cambridge, MA: The MIT Press.

J. Haveman and D. Hummels (2004), "Alternative hypotheses and the volume of trade: the gravity equation and the extent of specialization", *Canadian Journal of Economics*, *37*(1), 199–218.

K. Head, T. Mayer, and J. Ries (2010), "The erosion of colonial trade linkages after independence", *Journal of International Economics*, *81*(1), 1–14.

E. Helpman and P. Krugman (1987), *Market Structure and Foreign Trade: Increasing Returns, Imperfect Competition, and the International Economy*, *MIT Press Books*, vol. 1, The MIT Press.

H. L. Lee, V. Padmanabhan, and S. Whang (1997), "Bullwhip effect in supply chains", *Sloan Management Review*, *38*(3), 93–102.

A. A. Levchenko, L. T. Lewis, and L. L. Tesar (2010), “The collapse of international trade during the 2008-2009 crisis: In search of the smoking gun”, NBER Working Papers 16006, National Bureau of Economic Research, Inc.

M. J. Melitz (2003), “The impact of trade on intra-industry reallocations and aggregate industry productivity”, *Econometrica*, *71*(6), 1695–1725.

A. C. Molina and M. Fugazza (2009), “The determinants of trade survival”, IHEID Working Papers 05-2009, Economics Section, The Graduate Institute of International Studies.

J. Mora and W. Powers (2009), *The Costs of Adjustment to Trade Reform*, VOX.

K. O’Rourke (????), “Collapsing trade in a barbie world”, Tech. rep., www.irisheconomy.ie/index.php/(2009)/06/18/collapsing-trade-in-a-barbie-world.

P. K. Schott (2009), *US trade margins during the 2008 crisis*, VOX.

R. Wakasugi (2009), *Why was Japan’s trade hit so much harder?*, VOX.

7 Figures and tables

Figure 1: Finals vs. intermediates

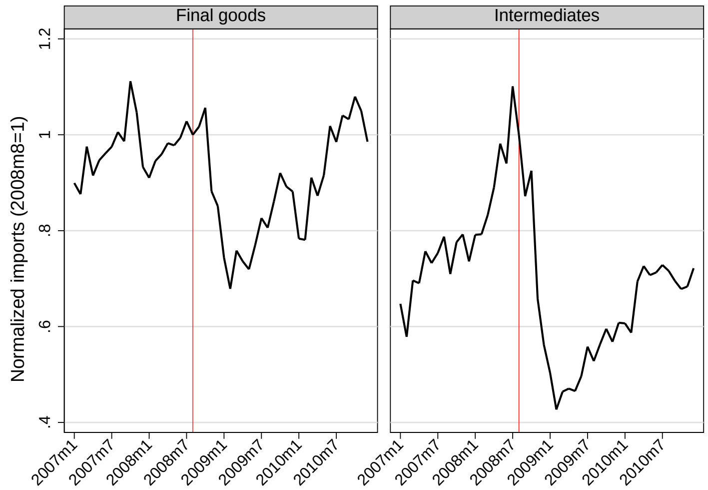
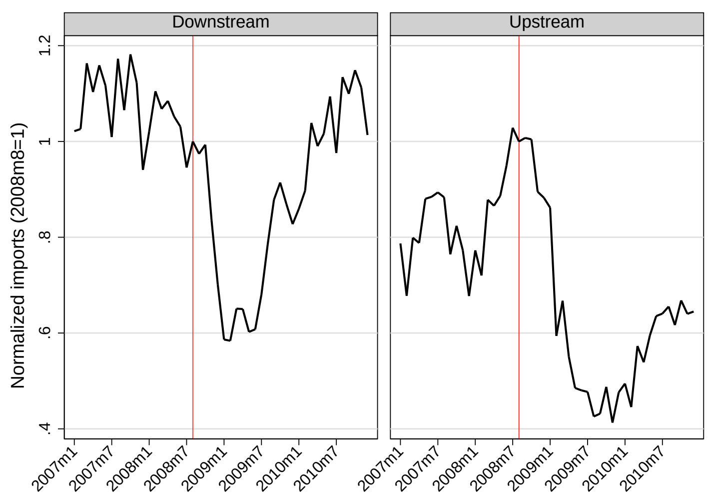


Figure 2: Downstream vs. upstream



Source: USITC and own calculations.

Figure 3: Deaths of trading relationships

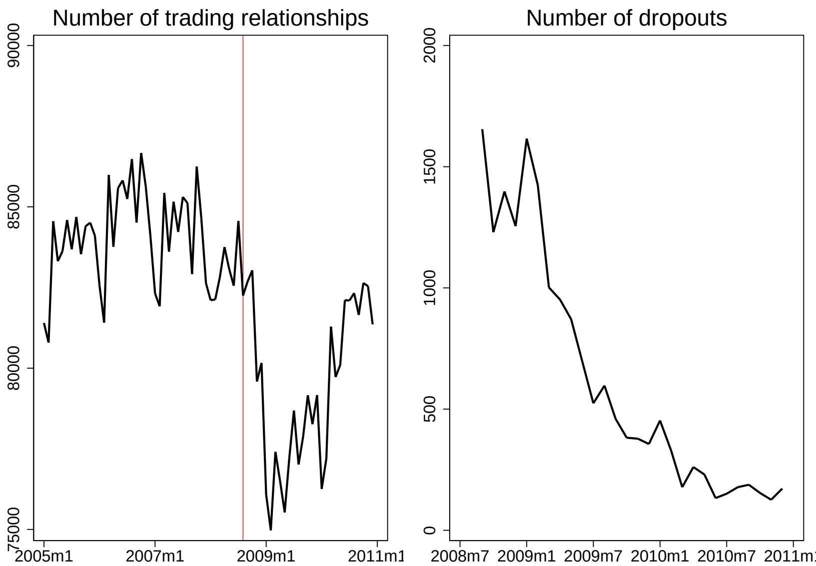
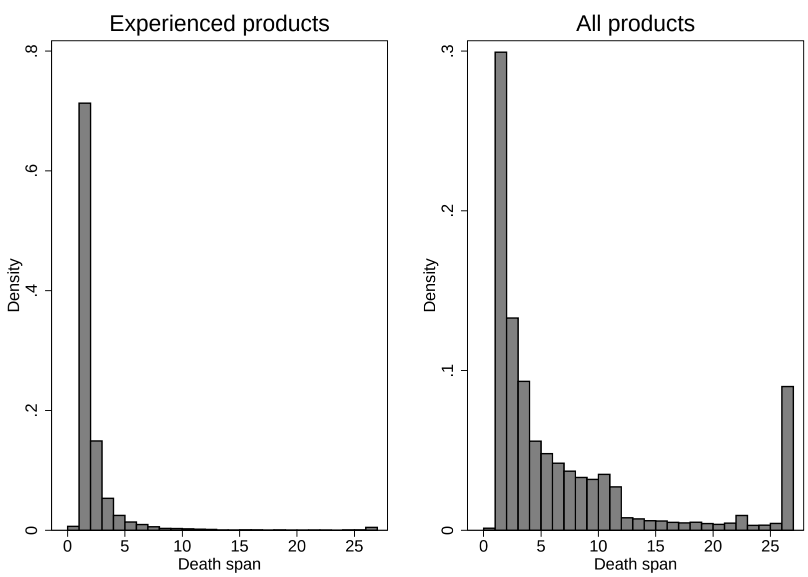
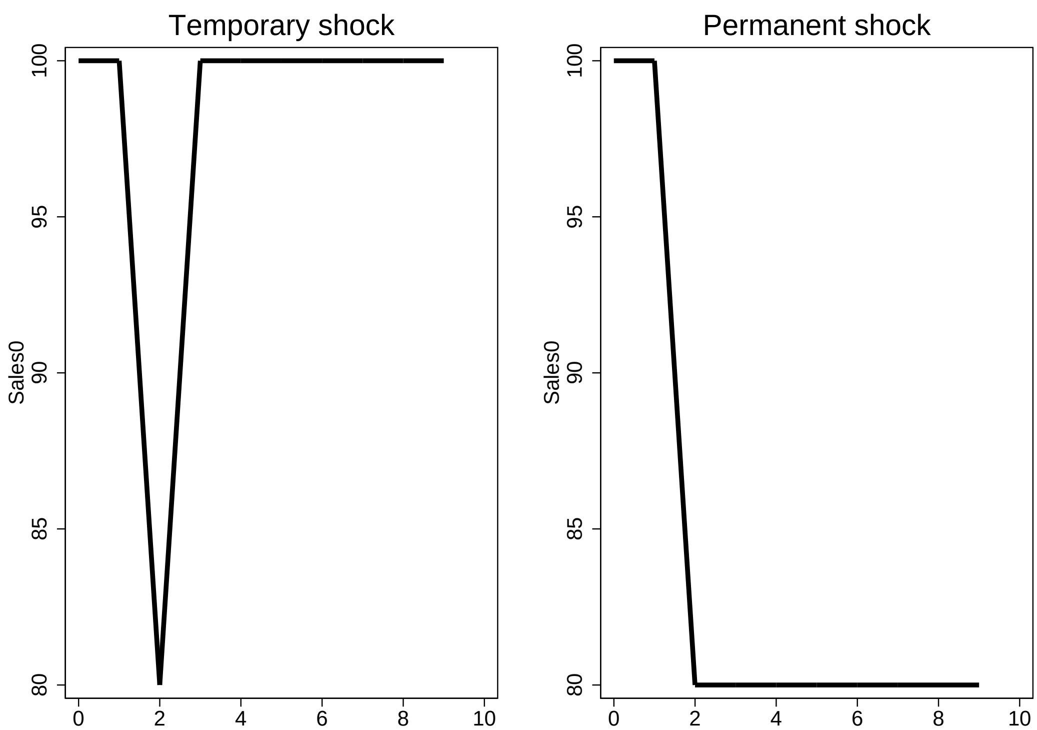


Figure 4: Resurrections of trading relationships



Source: USITC and own calculations.

Figure 5: Nature of the shocks



Source: own calculations.

Figure 6: Dynamics of sales with alpha=0.5

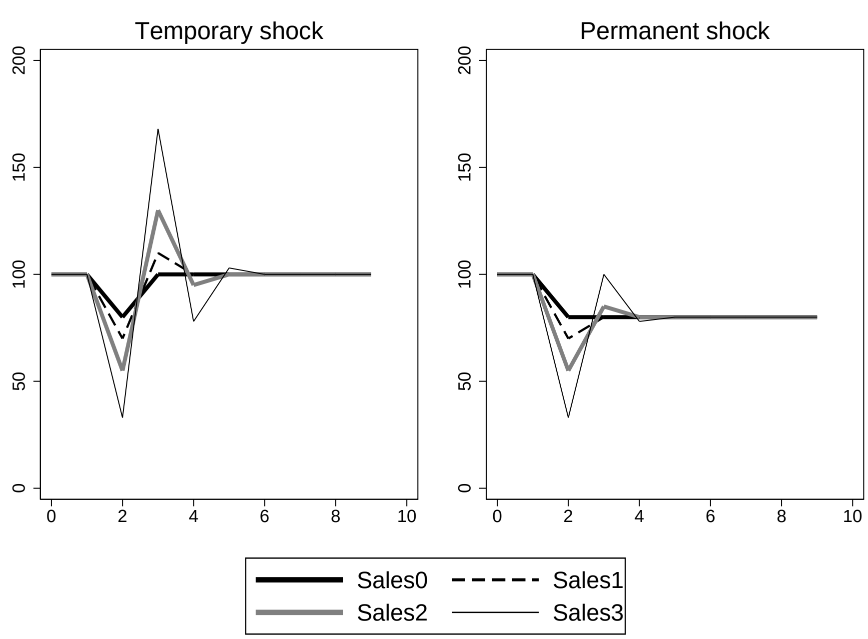
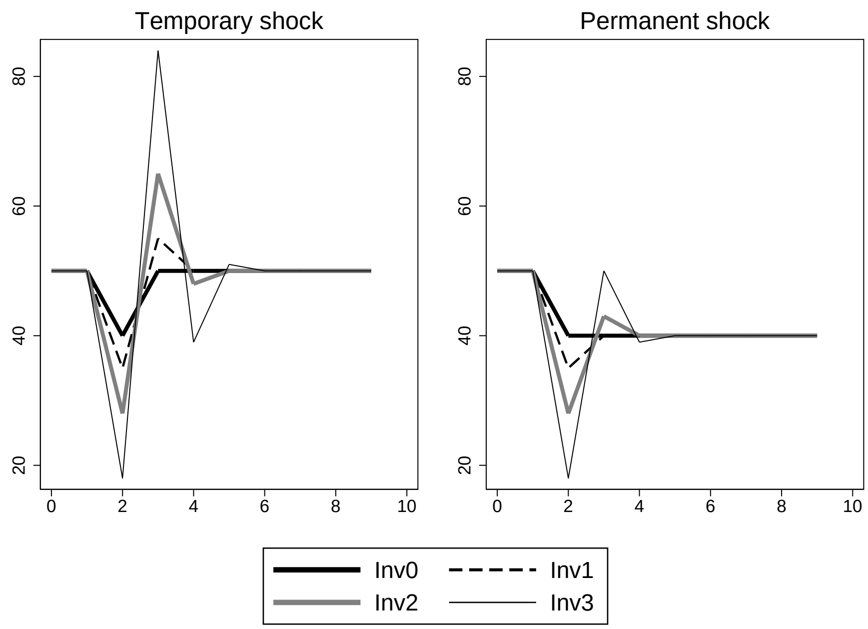


Figure 7: Dynamics of inventories with alpha=0.5



Source: own calculations.

Figure 8: Dynamics of sales with alpha=1

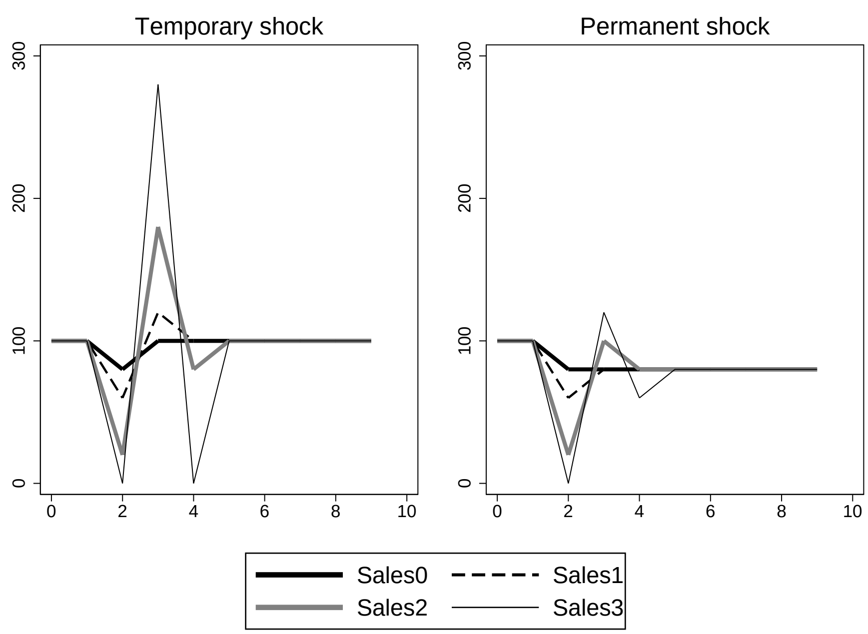
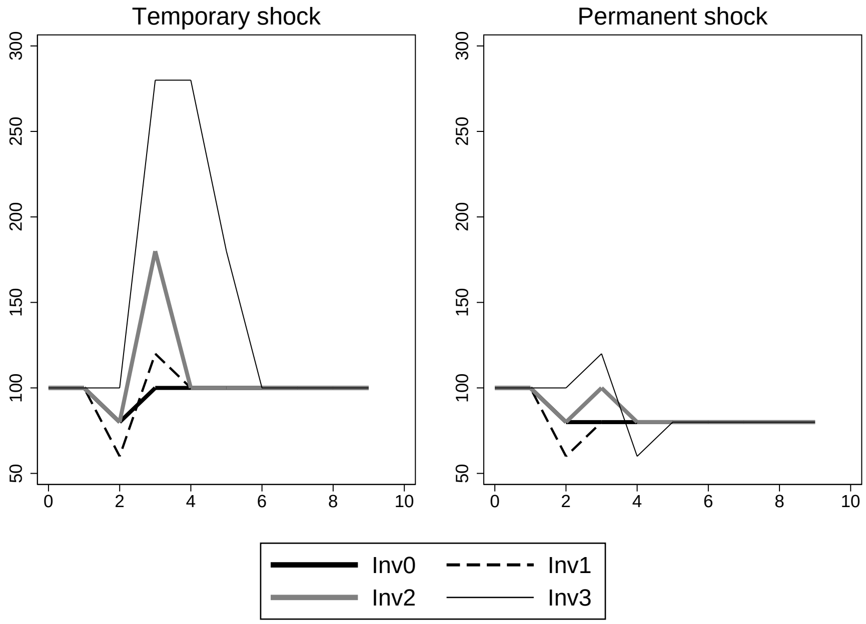


Figure 9: Dynamics of inventories with alpha=1



Source: own calculations.

Figure 10: Inventories to sales over time

Source: NBER CES manufacturing database.

Table 1: Countries in the sample

country	% US imports	N products	Upstreamness	Rank	Concentration	Rank	Alpha	Rank
Algeria	0.8%	38	3.19	42	0.08	5	0.01	6
Angola	0.6%	26	3.31	45	0.07	4	0.00	1
Argentina	0.2%	2,000	2.65	33	0.30	15	0.09	15
Australia	0.4%	3,270	2.22	28	0.50	27	0.15	42
Austria	0.4%	3,185	2.00	19	0.56	35	0.14	32
Belgium	0.8%	3,918	1.93	13	0.53	32	0.14	33
Brazil	1.5%	3,948	2.58	32	0.35	17	0.11	19
Canada	16.0%	7,088	2.67	35	0.30	14	0.08	12
Chile	0.5%	1,271	3.14	41	0.22	11	0.07	11
China	15.9%	7,798	1.65	5	0.68	43	0.14	35
Colombia	0.5%	2,045	2.67	34	0.24	12	0.04	8
Costa Rica	0.2%	1,149	1.85	10	0.56	34	0.09	17
Denmark	0.3%	2,775	1.78	8	0.64	42	0.16	43
Dominican Rep	0.2%	1,415	1.61	4	0.76	46	0.15	41
Ecuador	0.4%	922	3.00	40	0.13	9	0.01	5
Finland	0.3%	1,981	2.34	31	0.35	18	0.13	28
France	2.0%	6,219	2.04	20	0.51	28	0.17	47
Germany	4.8%	6,885	2.14	24	0.48	23	0.14	36
Hong Kong	0.4%	3,759	1.49	2	0.77	47	0.15	40
India	1.2%	5,269	1.74	7	0.69	44	0.16	44
Indonesia	0.7%	2,698	1.99	18	0.59	37	0.11	18
Ireland	1.5%	2,050	1.71	6	0.61	38	0.13	24
Israel	1.0%	3,053	1.49	1	0.79	48	0.18	48
Italy	1.8%	6,284	1.90	12	0.62	41	0.17	46
Japan	7.9%	6,314	1.97	17	0.52	31	0.13	27
Korea	2.5%	4,996	2.17	27	0.44	20	0.13	26
Kuwait	0.2%	81	3.34	47	0.07	1	0.00	4
Malaysia	2.0%	2,563	1.94	14	0.61	40	0.13	29
Mexico	10.4%	5,576	2.13	23	0.46	22	0.09	16
Netherlands	0.9%	4,350	2.22	29	0.45	21	0.11	20
Nigeria	1.5%	206	3.30	44	0.07	3	0.00	2
Norway	0.4%	1,718	2.74	36	0.20	10	0.07	10
Peru	0.3%	1,453	2.79	37	0.32	16	0.09	13
Philippines	0.5%	2,317	2.08	21	0.54	33	0.12	22
Russia	1.1%	1,486	2.95	39	0.12	8	0.09	14
Saudi Arabia	1.7%	386	3.33	46	0.07	2	0.00	3
Singapore	0.9%	2,271	1.97	16	0.50	26	0.13	23
South Africa	0.4%	2015	2.89	38	0.26	13	0.15	37
Spain	0.5%	4,537	2.13	22	0.49	25	0.14	34
Sweden	0.7%	3,289	1.96	15	0.52	29	0.15	38
Switzerland	0.8%	4,384	1.83	9	0.61	39	0.16	45
Taiwan	2.1%	5,092	2.16	25	0.49	24	0.13	30
Thailand	1.2%	3,570	1.86	11	0.59	36	0.13	25
Trin and Tobago	0.5%	387	3.37	48	0.08	7	0.04	9
Turkey	0.3%	2,565	2.24	30	0.52	30	0.15	39
United Kingdom	2.8%	6522	2.16	26	0.43	19	0.14	31
Venezuela	2.0%	830	3.20	43	0.08	6	0.02	7
Vietnam	0.5%	2,024	1.59	3	0.71	45	0.12	21

Source: USITC, NBER CES manufacturing database and own calculations.

Table 2: Sample industries and their technological measures

IO code	IO industry name	Upstreamness	Concentration	Alpha
336111	Automobile manufacturing	1.000	1.000	0.025
311111	Dog and cat food manufacturing	1.029	0.943	0.048
336112	Light truck and utility vehicle manufacturing	1.001	1.000	0.022
311330	Confectionery manufacturing from purchased chocolate	1.051	1.000	0.094
334300	Audio and video equipment manufacturing	1.133	0.428	0.104
315900	Apparel accessories and other apparel manufacturing	1.279	0.622	0.178
336411	Aircraft manufacturing	1.283	0.476	0.521
325412	Pharmaceutical preparation manufacturing	1.309	0.622	0.117
333295	Semiconductor machinery manufacturing	1.520	0.947	0.203
326210	Tire manufacturing	1.938	0.519	0.080
335120	Lighting fixture manufacturing	2.018	0.643	0.147
32712A	Brick, tile, and other structural clay product manufacturing	2.288	1.000	0.215
336300	Motor vehicle parts manufacturing	2.295	0.225	0.086
324110	Petroleum refineries	2.396	0.132	0.070
332500	Hardware manufacturing	2.549	0.295	0.132
325510	Paint and coating manufacturing	2.691	0.437	0.116
336412	Aircraft engine and engine parts manufacturing	2.694	0.168	0.202
325320	Pesticide and other agricultural chemical manufacturing	2.844	0.071	0.115
336413	Other aircraft parts and auxiliary equipment manufacturing	2.430	0.245	0.319
327310	Cement manufacturing	2.986	0.193	0.163
325212	Synthetic rubber manufacturing	3.048	0.192	0.134
33131B	Aluminum product manufacturing from purchased aluminum	3.137	0.167	0.134
325120	Industrial gas manufacturing	3.226	0.928	0.051
325182	Carbon black manufacturing	3.419	0.157	0.092
331200	Steel product manufacturing from purchased steel	3.450	0.129	0.168
325910	Printing ink manufacturing	3.488	0.065	0.111
331420	Copper rolling, drawing, extruding and alloying	3.611	0.176	0.112
325181	Alkalies and chlorine manufacturing	3.611	0.369	0.084
325310	Fertilizer manufacturing	3.762	0.060	0.100
33131A	Alumina refining and primary aluminum production	3.814	0.058	0.111
331411	Primary smelting and refining of copper	4.355	0.123	0.077
325110	Petrochemical manufacturing	4.651	0.083	0.099

Source: USITC, NBER CES manufacturing database and own calculations.

Table 3: Descriptives of the technological measures

Descriptives					
	N	**Mean**	**Std. Dev.**	**Min**	**Max**
Upstreamness	425	2.09	0.85	1	4.65
Concentration	425	0.58	0.36	0	1
Alpha	279	0.14	0.06	0	0.52
Correlations					
	Upstreamness	**Concentration**			
Concentration	-0.719				
	(0.000)				
Alpha	-0.127	0.030			
	(0.034)	(0.619)			

Source: USITC, NBER CES manufacturing database and own calculations.

Table 4: Correlations of different definitions of inventories to sales

	Average	Median	1960s	1970s	1980s
Median	0.99				
1960s	0.92	0.94			
1970s	0.97	0.98	0.95		
1980s	0.96	0.95	0.83	0.92	
1990s	0.92	0.87	0.71	0.81	0.90

This table summarises the correlations of inventories-to-sales ratios computed over different decades or as an average or median over the whole period 1958-2005. Source: NBER CES manufacturing database.

Table 5: Glejser second stage with different crisis windows

	(1) 2009m4	(2) 2009m12	(3) 2010m6	(4) 2010m12
Upstreamness*Crisis	0.0584***	0.0456***	0.0286**	0.0162
	(0.0140)	(0.0122)	(0.0113)	(0.0110)
Concentration*Crisis	0.0162	0.00264	-0.0123	-0.0266
	(0.0347)	(0.0299)	(0.0283)	(0.0273)
Alpha*Crisis	0.426***	0.589***	0.570***	0.468***
	(0.150)	(0.141)	(0.133)	(0.125)
Constant	0.906***	0.888***	0.946***	1.015***
	(0.0530)	(0.0480)	(0.0453)	(0.0445)
Observations	447,476	512,268	560,862	609,456
R-squared	0.607	0.598	0.595	0.593
Time FE	YES	YES	YES	YES
HS8 FE	YES	YES	YES	YES
Cluster	Industry	Industry	Industry	Industry

Note: Results from the second stage of the Glejser test. Each column refers to a different crisis window. The dependent variables are the absolute values of the residuals from the first stage. All regressions include the time and product fixed effects, coefficients not reported. Standard errors in parentheses. Significance (p-value): *10%, **5%, ***1%;

Table 6: Glejser robustness tests

	(1)	(2)	(3)	(4)
	2009m4	2010m12	2009m4	2010m12
	DL12	DL12	HP	HP
Upstreamness*Crisis	0.0515**	0.0223	0.0392**	0.00564
	(0.0246)	(0.0210)	(0.0174)	(0.0163)
Concentration*Crisis	-0.0185	-0.0775	-0.0461	-0.0782*
	(0.0612)	(0.0517)	(0.0430)	(0.0404)
Alpha*Crisis	0.0573	0.572**	0.422**	0.647***
	(0.273)	(0.234)	(0.179)	(0.193)
Constant	1.200***	1.127***	0.928***	0.872***
	(0.0940)	(0.0818)	(0.0646)	(0.0637)
Observations	447,476	609,456	447,476	609,456
R-squared	0.383	0.366	0.583	0.557
Time FE	YES	YES	YES	YES
HS8 FE	YES	YES	YES	YES
Cluster	Industry	Industry	Industry	Industry

Note: Robustness tests from the second stage of the Glejser test. The dependent variables are the absolute values of the residuals from the first stage. First two columns amend the first stage by using export growth as dependent variable. Last two columns based on a one stage estimation with HP filtered exports as dependent variable. All regressions include the time and product fixed effects, coefficients not reported. Standard errors in parentheses. Significance (p-value): *10%, **5%, ***1%.

Table 7: Probability of a trading death

	(1)	(2)	(3)	(4)
Experience	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
Market share	-0.030***	-0.030***	-0.032***	-0.033***
	(0.000)	(0.002)	(0.001)	(0.001)
Upstreamness	0.013***	0.013***	0.014***	0.016***
	(0.004)	(0.005)	(0.004)	(0.004)
Concentration	0.026**	0.026**	0.028**	0.026**
	(0.011)	(0.011)	(0.011)	(0.011)
Alpha	0.208***	0.208***	0.220***	0.225***
	(0.040)	(0.044)	(0.042)	(0.043)
Observations	301,301	301,301	301,301	301,301
R-squared	0.051	0.051	0.0394	0.0359
Country effect	YES	YES	YES	NO
Clustering	Industry	C-I	Industry	Industry
Method	LPM	LPM	Probit	Probit

Note: The dependent variable is a dummy equal to one if the product dropped out of trading in the period September 2008 to April 2009. All regressions include country fixed effects, coefficients not reported. C-I stands for Country-Industry. LPM refers to linear probability model. Standard errors in parentheses. Significance (p-value): *10%, **5%, ***1%.

Table 8: Probability of a trading resurrection

	(1)	(2)	(3)
Experience	0.007***	0.007***	0.009***
	(0.000)	(0.000)	(0.000)
Market share	-0.004***	-0.004***	-0.005***
	(0.000)	(0.001)	(0.001)
Upstreamness	-0.008***	-0.008***	-0.006***
	(0.002)	(0.003)	(0.002)
Concentration	0.001	0.001	0.001
	(0.006)	(0.006)	(0.004)
Alpha	0.013	0.013	0.013
	(0.024)	(0.029)	(0.018)
Observations	208,746	208,746	208,746
R-squared	0.071	0.071	0.137
Country effect	YES	YES	YES
Clustering	Industry	C-I	Industry
Method	LPM	LPM	Probit

Note: The dependent variable is a dummy equal to one if a product that dropped out of trading in the period September 2008 to April 2009 returned back to trading before the end of 2010. All regressions include country fixed effects, coefficients not reported. LPM refers to linear probability model. C-I stands for Country-Industry. Standard errors in parentheses. Significance (p-value): *10%, **5%, ***1%.

Table 9: Does origin matter for drop out?

	(1) *Contiguity*	(2) *Common language*	(3) *Distance*	(4) *GDP*	(5) *RTA*
Experience	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market share	-0.030***	-0.030***	-0.030***	-0.029***	-0.030***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Upstreamness	0.013***	0.017***	0.019***	0.008	0.014***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.005)
Concentration	0.026**	0.026**	0.026**	0.024**	0.026**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Alpha	0.208***	0.208***	0.208***	0.212***	0.208***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Ups*Country Char	0.004	-0.008*	-0.000	0.000	-0.003
	(0.003)	(0.005)	(0.000)	(0.000)	(0.004)
Constant	0.515***	0.506***	0.513***	0.526***	0.513***
	(0.018)	(0.018)	(0.018)	(0.020)	(0.018)
Observations	301,301	301,301	301,301	283,507	301,301
R-squared	0.051	0.051	0.051	0.051	0.051
Country effect	YES	YES	YES	YES	YES
Clustering	C-I	C-I	C-I	C-I	C-I
Method	LPM	LPM	LPM	LPM	LPM

Note: The dependent variable is a dummy equal to one if a product that dropped out of trading in the period September 2008 and April 2009. Ups*Country Char refers to an interaction of Upstreamness with the country characteristic listed at the top of each column. All regressions include country fixed effects, coefficients not reported. C-I stands for Country-Industry. LPM refers to linear probability model. Standard errors in parentheses. Significance (p-value): *10%, **5%, ***1%.

Table 10: Does origin matter for resurrection?

	(1) *Contiguity*	(2) *Common language*	(3) *Distance*	(4) *GDP*	(5) *RTA*
Experience	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market share	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Upstreamness	-0.008***	-0.006**	-0.008	-0.009*	-0.008***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)
Concentration	0.001	0.001	0.001	0.004	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Alpha	0.013	0.013	0.013	0.009	0.012
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Ups*Country Char	0.008**	-0.004	0.000	0.000	0.003
	(0.004)	(0.004)	(0.000)	(0.000)	(0.004)
Constant	0.661***	0.656***	0.660***	0.661***	0.661***
	(0.013)	(0.013)	(0.013)	(0.015)	(0.013)
Observations	208,746	208,746	208,746	196,516	208,746
R-squared	0.071	0.071	0.071	0.071	0.071
Country effect	YES	YES	YES	YES	YES
Clustering	C-I	C-I	C-I	C-I	C-I
Method	LPM	LPM	LPM	LPM	LPM

Note: The dependent variable is a dummy equal to one if a product that dropped out of trading in the period September 2008 to April 2009 and returned to trading before the end of 2010. Ups*Country Char refers to an interaction of Upstreamness with the country characteristic listed at the top of each column. All regressions include country fixed effects, coefficients not reported. C-I stands for Country-Industry. LPM refers to linear probability model. Standard errors in parentheses. Significance (p-value): *10%, **5%, ***1%.

Table 11: Does experience matter?

	(1) Small drop	(2) Large drop	(3) Small resurrection	(4) Large resurrection
Experience	-0.061***	-0.060***	-0.246***	0.001***
	(0.006)	(0.002)	(0.008)	(0.000)
Market share	-0.026***	-0.011***	0.013***	-0.002***
	(0.004)	(0.001)	(0.004)	(0.000)
Upstreamness	0.022***	-0.001	-0.014**	-0.003
	(0.006)	(0.005)	(0.007)	(0.002)
Concentration	0.050***	-0.038***	-0.019	0.006
	(0.019)	(0.015)	(0.018)	(0.004)
Alpha	0.198***	-0.019	0.056	-0.003
	(0.053)	(0.060)	(0.070)	(0.018)
Observations	69,847	77,148	38,544	43,390
R-squared	0.010	0.388	0.091	0.028
Country effect	YES	YES	YES	YES
Clustering	C-I	C-I	C-I	C-I
Method	LPM	LPM	LPM	LPM

Note: Drop out and resurrection regressions split by the Experience variable. Small refers to the bottom quartile and large to the top quartile of pre-crisis experience. All regressions include country fixed effects, coefficients not reported. C-I stands for Country-Industry. LPM refers to linear probability model. Standard errors in parentheses. Significance (p-value): *10%, **5%, ***1%.

Table 12: Does size matter?

	(1) Small drop	(2) Large drop	(3) Small resurrection	(4) Large resurrection
Experience	0.019***	-0.012***	0.012***	0.004***
	(0.001)	(0.001)	(0.000)	(0.000)
Market share	-1.844**	-0.017***	1.008	-0.001*
	(0.869)	(0.001)	(0.796)	(0.001)
Upstreamness	0.021***	0.029***	-0.015***	-0.004
	(0.007)	(0.009)	(0.005)	(0.003)
Concentration	0.058***	-0.009	-0.003	-0.003
	(0.020)	(0.023)	(0.014)	(0.008)
Alpha	0.166***	0.294***	-0.021	0.057
	(0.051)	(0.085)	(0.066)	(0.035)
Observations	77,800	75,285	54,148	42,218
R-squared	0.052	0.162	0.040	0.058
Country effect	YES	YES	YES	YES
Clustering	C-I	C-I	C-I	C-I
Method	LPM	LPM	LPM	LPM

Note: Drop out and resurrection regressions split by the Market share variable. Small refers to the bottom quartile and large to the top quartile of pre-crisis market share. All regressions include country fixed effects, coefficients not reported. C-I stands for Country-Industry. LPM refers to linear probability model. Standard errors in parentheses. Significance (p-value): *10%, **5%, ***1%.

Table 13: Aggregation

VARIABLES	(1) HS8 drop	(2) HS6 drop	(3) HS4 drop
Experience	-0.003***	-0.006***	-0.012***
	(0.001)	(0.001)	(0.001)
Marketshare	-0.030***	-0.030***	-0.027***
	(0.002)	(0.002)	(0.004)
Upstreamness	0.013***	0.009**	0.015**
	(0.005)	(0.004)	(0.006)
Concentration	0.026**	0.018	0.032*
	(0.011)	(0.014)	(0.018)
Alpha	0.208***	0.104**	-0.051
	(0.044)	(0.045)	(0.064)
Observations	301,301	200,522	60,438
R-squared	0.051	0.094	0.213
Country effect	YES	YES	YES
Clustering	C-I	C-I	C-I
Method	LPM	LPM	LPM

Note: Probability to drop out at different levels of HS aggregation. All regressions include country fixed effects, coefficients not reported. C-I stands for Country-Industry. LPM refers to linear probability model. Standard errors in parentheses. Significance (p-value): *10%, **5%, ***1%