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Large Firm Dynamics and Secular Stagnation: Evidence from Japan and the U.S.

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Large Firm Dynamics and Secular Stagnation: Evidence from Japan and the U.S.*

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Abstract

Focusing on the recent secular stagnation debate, this paper examines the role of large firm dynamics as determinants of productivity fluctuations. We first show that idiosyncratic shocks to large firms as well as entry, exit, and reallocation effects account for 30 to 40 percent of productivity fluctuations in Japan and the U.S. Second, since the mid-2000s, the slowdown in large foreign firm entry into the U.S. has led to a decline in business dynamics and downward pressures on productivity growth. Third, we identify demand and supply shocks by matching idiosyncratic large-firm shocks in the granular residual (Gabaix, 2011) and changes in sectoral inflation rates and show that the prolonged slowdown in productivity growth in Japan and the U.S. was mostly driven by supply shocks. Overall, our results support the supply-side views of Gordon (2012, 2015, 2016) in the secular stagnation debate.

Key Words: Granular Hypothesis; Entry-Exit; Productivity Growth; Secular Stagnation

JEL Classification: E13, E23, E32, D21

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1 Introduction

Since the 2008 global financial crisis, there is an ongoing debate on why economic growth — especially productivity growth — in industrialized countries has remained so low for such a prolonged period. The recent debate has focused mainly on slowdowns of productivity growth in the U.S. and Europe since the global financial crisis, but within industrialized economies, Japan is a well-known example where productivity growth has declined since the 1980s.[1]

One of the fundamental questions of the recent debate is whether this persistent slow growth is driven by demand or supply factors. Summers (2014, 2015, 2016) has focused on the demand side to explain *secular stagnation* — a concept originally introduced by Hansen (1939) —, arguing that a prolonged shortage of investment demand has led to hysteresis effects[2] and has ultimately resulted in what is called an inverse Say's Law: "A lack of demand creates a lack of supply potential." While this has not been the conventional view in mainstream macroeconomics, the idea kicked off an active debate in the search for explanations for the observed slow growth since the global financial crisis.[3] A rather traditional macroeconomic approach to the secular stagnation debate is the supply-side view expressed by Gordon (2012, 2015). The supply-side view argues that the fruits of the information-technology revolution had already materialized by the mid-2000s (Fernald 2015, Byrne, Fernald, and Reinsdorf 2016) and that a decline in business dynamism may also be a source of today's secular stagnation.[4] Although both views are

[1] Hayashi and Prescott (2002) kicked off the discussion of the "lost decade" of the 1990s in Japan, where they showed using growth accounting frameworks that most of the decline in economic growth was due to a slowdown in TFP growth. Many studies have followed since then, for example, Fukao et al. (2004), Jorgenson and Motohashi (2005), Jorgenson and Nomura (2007), Kawamoto (2005), among others.

[2] The possible role of hysteresis effects was first discussed by Blanchard and Summers (1986) in relation to unemployment in Europe. In their study, they argued that recessions have lasting effects and are the root cause of lower output in later periods.

[3] See Teulings and Baldwin (2014) for a comprehensive discussion on this topic.

[4] Other possible explanations for secular stagnation include a debt overhang (Lo and Rogoff, 2015), a savings glut (Bernanke, 2015), or a liquidity trap (Krugman, 2013).

not mutually exclusive, further empirical evidence on the origins of productivity growth is needed to assess whether demand or supply is the dominant factor in explaining the secular stagnation phenomenon.

Against this background, the aim of this paper is to examine the secular stagnation phenomenon by focusing on the role of large firm dynamics as a determinant of productivity fluctuations. Large firm dynamics are indeed important profiles of economic fluctuations, as documented in, for example, Canals et al. (2007) where they show that the top 10 exporters account for about 30 percent of Japan's total exports. We will use firm-level data from Japan and the U.S. and proceed in several steps. First, we calibrate the Carvalho and Grassi (2016) model to Japanese data to demonstrate that idiosyncratic shocks to large firms have a non-negligible impact on the macroeconomy. Second, we empirically investigate how various aspects of large firm dynamics — idiosyncratic shocks to large firms, the entry and exit of firms, and the reallocation of resources across firms — have contributed to productivity growth in both countries. Third, we identify demand and supply shocks by matching idiosyncratic large firm shocks in the granular residual with changes in sectoral inflation rates, and examine their impact on productivity. Overall, our results support the supply-side view of Gordon (2012, 2015, 2016) in the secular stagnation debate.

One of the most influential ideas from the recent literature on firm dynamics is the *granular hypothesis* introduced by Gabaix (2011).[5] The granular hypothesis holds that idiosyncratic shocks to large firms have macroeconomic effects. More specifically, when the firm size distribution is fat-tailed, the central limit theorem breaks down, and idiosyncratic shocks to large firms propagate to the aggregate level. Gabaix (2011) provides the foundations for this hypothesis and shows that idiosyncratic shocks to large firms are indeed the underlying sources of productivity fluctuations. The granular hypothesis has

[5] Other studies that worked on the granular hypothesis include Acemoglu et al. (2012), di Giovanni and Levchenko (2012), Carvalho and Gabaix (2013) and di Giovanni, Levchenko, and Mejean (2014), among others.

sparked further theoretical developments such as the model proposed by Carvalho and Grassi (2016), in which they examine the role of firm size distributions in the neo-classical firm sector model of Hopenhayn (1992) to analyze the impact of large firm shocks on aggregate fluctuation. Their calibration exercise shows that the model performs well in replicating the business cycle moments of the U.S. economy. In this paper, we will first calibrate this Carvalho–Grassi model to Japanese data and show that the model performs well for Japan as well. These theoretical results support the view that idiosyncratic shocks to large firms are indeed an important source of productivity fluctuations. Gabaix (2011) also shows empirically that idiosyncratic shocks to the top 100 firms — measured by the granular residual — account for 30 to 40 percent of overall productivity fluctuation in the U.S. Given the good fit of granular regressions, we use this approach to pin down the origins of productivity growth using firm-level data for Japan and the U.S.

Other aspects of large firm dynamics include the entry and exit of firms and allocative efficiency across existing firms — which we will call reallocation —. Entry, exit, and reallocation effects can be regarded as proxies for the degree of business dynamism. Based on a thorough review of the literature, Foster, Haltiwanger, and Krizan (2001) reach the conclusion that increases in net entry has a positive effect on aggregate productivity growth. More recently, Clementi and Palazzo (2016), building on Hopenhayn (1992), have also shown that positive aggregate productivity shocks induce entry and that such entry propagates the effects of productivity shocks. Their calibration exercise shows that, conditional on survival, entrants grow faster than exiters, so that net entry has a positive effect on productivity growth. They further conclude that the drop in the number of establishments was partly responsible for the low growth following the Great Recession. In light of these findings, we employ the dynamic Olley–Pakes productivity decomposition recently proposed by Melitz and Polanec (2015) using firm-level data for Japan and the U.S. to examine how the business dynamics of large firms affected productivity growth.

We examine the secular stagnation phenomenon by identifying demand and supply shocks using the granular residual. More specifically, we match the idiosyncratic firm-level shocks in the granular residual with changes in sectoral inflation rates for identification:[6] when output and inflation simultaneously move in the same direction, this is considered as a demand shock, and when output and inflation move in opposite directions, this is considered as a supply shock.[7] After identifying these shocks from the granular residual, we conduct granular regressions and examine the impulse responses from local projections to see how these shocks affect productivity.

Our empirical findings can be summarized as follows. First, idiosyncratic shocks to large firms, firm entry and exit, and reallocation account for 30 to 40 percent of productivity fluctuations in Japan and the U.S. Second, in contrast with the U.S., the contribution of firm net entry in Japan is small. The IT revolution led many large foreign firms to enter the U.S. during the late 1990s to the mid-2000s — especially firms in the telecommunications sector — and this had a positive effect on productivity growth. However, since the Great Recession, the entry of foreign firms into the U.S. has slowed, reducing the degree of business dynamism and ultimately exerting downward pressure on productivity growth. Third, in Japan, total factor productivity (TFP) growth is mainly driven by large firms in the transport equipment, electronic components and devices, and information technology industries. For the U.S., the main drivers are large firms belonging to the durables and the information technology industries. Fourth, our identified demand and supply shocks show that the prolonged productivity slowdown both in Japan and the U.S. was mostly due to supply shocks, which supports the supply-side view of Gordon (2012, 2015, 2016) in the secular stagnation debate.

[6] Identification using inflation data is common in the literature. See, e.g., Summers (2015, 2016), and Blanchard, Cerutti, and Summers (2015).

[7] In a broad class of models, technology shocks lead to a reduction in inflation, as shown by Gali (1999) and Gali and Rabanal (2004), among others.

The organization of the paper is as follows. Section 2 describes the Carvalho–Grassi model (Carvalho and Grassi, 2016). Section 3 calibrates the Carvalho–Grassi model to Japanese data and runs business cycle simulations. Section 4 performs the dynamic Olley–Pakes decomposition of aggregate labor productivity and granular regressions. Section 5 identifies demand and supply shocks using the granular residual and investigates their impact on productivity growth. Section 6 concludes.

2 The Carvalho–Grassi Model

In order to examine how idiosyncratic shocks to large firms, firm entry and exit, and reallocation affect aggregate fluctuations, we employ Carvalho and Grassi's (2016) model, referred to as the CG model hereafter. The CG model builds on Hopenhayn's (1992) model and incorporates firm size distributions into a standard neo-classical firm sector model with optimal entry and exit decisions. As documented in Axtell (2001), firm size distributions are indeed fat-tailed and well described by a power-law distribution. Incorporating firm size distributions into a neo-classical model entails complexity, but the novel feature of the CG model is its tractability. The model also generates rich firm dynamics, which makes it suitable for analyzing large firm dynamics. In this section, we describe the basic setup of the CG model.

There are two broad types of firms: incumbents and potential entrants. The CG model incorporates firm size distributions μ by assuming that firms are distributed over an exponentially constructed productivity space $\Phi = \{\varphi^1, ..., \varphi^S\}$, where φ is the increment of this space.

2.1 Incumbents' Problem

In each period, incumbents face the choice whether to continue their business or not. They first observe the aggregate real wage $w(\mu)$, which is taken to be the state variable mapped from the firm distribution,[8] and draw their idiosyncratic productivity level ϕ^s from the productivity space Φ. For example, if the real wage is high and the idiosyncratic productivity draw is low, it will not be profitable for that firm to continue, so it will shut down its business and exit from the economy. More formally, the instantaneous payoff of an incumbent firm is given by

$$\pi^*\Big(w(\mu), \varphi^s\Big) = \max_n \{\varphi^s n^\alpha - w(\mu)n - c_f\},$$

where n is labor input for production and c_f is the fixed cost for production. In this setting, the value function for the incumbent $V\Big(w(\mu), \varphi^s\Big)$ is given by the following Bellman equation:

$$V\Big(w(\mu), \varphi^s\Big) = \pi^*\Big(w(\mu), \varphi^s\Big) + \max_{\{Exit,Stay\}} \Big\{0, \beta \int_{\mu' \in \Lambda} \sum_{\varphi^{s'} \in \Phi} V\Big(w'(\mu'), \varphi^{s'}\Big) F(\varphi^{s'}|\varphi^s)\Gamma(d\mu'|\mu)\Big\},$$

where β is the discount factor, and $\Gamma(.|\mu)$ and $F(.|\varphi^s)$ are the conditional distribution of μ' and the idiosyncratic productivity draw in the next period, φ', respectively.

2.2 Entrants' Problem

There are M potential entrants, which are distributed over the productivity space Φ, where the cumulative distribution function is given by G_S. We assume that this distribution is exogenous and is Pareto. Firms enter the economy iff:

$$V^e\Big(w(\mu), \varphi^e\Big) = \beta \int_{\mu' \in \Lambda} \sum_{\varphi^{e'} \in \Phi} V\Big(w(\mu'), \varphi^{e'}\Big) F(\varphi^{e'}|\varphi^e)\Gamma(d\mu'|\mu) > c_e,$$

where c_e is the entry cost. As we will see later, in equilibrium, firms beyond a certain productivity threshold will enter.

[8] Carvalho and Grassi (2016) take the firm distribution as the state variable, but the distribution can be mapped to real wages to reduce the computational burden.

2.3 Aggregation and the Labor Market

Since all firms are distributed over the productivity space Φ, the aggregate productivity level can be expressed as the weighted average over the firm distribution μ_t. That is, aggregate productivity A_t will be given by

$$A_t = \Big(\sum_{s=1}^{S} \mu_{s,t}(\varphi^s)^{\frac{1}{1-\alpha}}\Big)^{1-\alpha} = (B'\mu_t)^{1-\alpha},$$

where $\mu_{s,t}$ is the mass of firms in grid s at time t, and $B' = \{(\varphi^1)^{\frac{1}{1-\alpha}}, ..., (\varphi^S)^{\frac{1}{1-\alpha}}\}$ is a vector of productivity levels. We define $T = B'\mu$ as a monotone transformation of productivity for computational convenience. In this setting, the aggregate production function will be $Y_t = A_t(L_t^D)^\alpha$, where L_t^D denotes aggregate labor demand.

Labor supply is given exogenously as $L^S(w_t) = Nw_t^\gamma$, where N denotes the total number of firms. From firms' optimization, labor demand will satisfy the first order condition of the instantaneous payoff function of incumbent firms, so the aggregate labor demand will be

$$L^D(w_t) = \Big(\frac{\alpha A_t}{w_t}\Big)^{\frac{1}{1-\alpha}}.$$

2.4 Equilibrium

We focus on a competitive equilibrium where incumbents and potential entrants follow an entry-exit cutoff rule, $s^*(\mu^*, \phi)$. That is, incumbent firms continue their business if their idiosyncratic productivity draw φ^s exceeds the cutoff threshold φ^{s^*}. Likewise, potential entrants enter if their productivity draw exceeds this threshold. We solve incumbent firms' optimization problem using value function iteration.

Equilibrium will consist of the optimal entry-exit rule $s^*(\mu^*, \phi)$ for incumbents and entrants, a stationary distribution μ^* with positive entry satisfying entrants' incentive constraints, aggregate quantities A^*, Y^*, L^*, and wages w^* clearing the labor market.

2.5 Transition Probabilities

We add more structure to the CG model to apply the main theoretical results from Carvalho and Grassi (2016). We assume that the idiosyncratic productivity draws of incumbents follow a Markov process of the form

$$\mathbf{P} = \begin{bmatrix} a+b & c & 0 & \dots & \dots & 0 & 0 \\ a & b & c & \dots & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots & 0 & 0 \\ 0 & 0 & 0 & \dots & a & b & c \\ 0 & 0 & 0 & \dots & 0 & a & b+c \end{bmatrix}_{(S \times S)} .$$

Rows of this matrix represent firms entering in period t with idiosyncratic productivity draw ϕ^s, columns represent the next period's productivity draw $\phi^{s'}$, and a, b, and c represent transition probabilities. Theorem 2 in Carvalho and Grassi (2016) shows that when the productivity process takes the above form and entrants' distribution is assumed to be Pareto ($G_s = K_e(\phi^s)^{-\delta_e}$), the productivity process $T_t = B'\mu_t$ will follow an AR(1) process:

$$\begin{aligned} T_{t+1} &= \rho T_t + \rho E_t(\varphi) + O_t^T + \sigma_t \varepsilon_{t+1}, \\ \sigma_t^2 &= \varrho D_t + \varrho E_t(\varphi^2) + O_t^\sigma, \end{aligned} \tag{1}$$

where $E[\varepsilon_{t+1}] = 0$ and $V[\varepsilon_{t+1}] = 1$. $E_t(\varphi)$ represents the contribution of net entry, D_t represents the quadratic expectations with respect to idiosyncratic productivity, and O_t^T and O_t^σ are correction terms.

3 Simulation Analysis

In this section, we calibrate the CG model to the Japanese economy to simulate how large firm shocks propagate to the macroeconomy. The calibrated parameters are summarized in Table 1. We use standard parameter values for the discount rate and labor elasticity, while the labor share matches the data from the national accounts. Parameters for the firm distribution and the productivity space were estimated following Axtell (2001). Using the calculated distribution, transition probabilities are calibrated so that the firm distribution in equilibrium matches the firm distribution from the data averaged over time. The number of total firms is set to the size of Japan's publicly listed firms.[9]

Table 1: Calibrated Parameters

Parameter	Value	Description
S	40	Size of the productivity space
ϕ	1.085	Grids of the productivity space
a	0.613	Markov transition probability
c	0.387	Markov transition probability
β	0.95	Discount rate
γ	2	Elasticity of labor
α	0.613	Labor share
M	500	Number of potential entrants
N	3000	Number of total firms
δ_e	1.84	Pareto tail parameter of potential entrants
δ	1.50	Pareto tail parameter of all firms

Figure 1 compares the steady state firm distribution μ^* — i.e., the counter cumulative distribution (CCD) — from the model and the Japanese data, and we can see that the two are very similar. A detailed description of the data is provided in Section 4.1.

[9]Since there is no available data on the potential number of entrants, we have assumed that the number is 500, but this assumption does affect our main results.

3.1 Business Cycle Characteristics

We run stochastic simulations around the steady state to calculate the business cycle statistics from the CG model. In the current set up, the firm distribution follows

$$\mu_{t+1} = m(\mu_t) + \epsilon_{t+1}, \tag{2}$$

where $m(\mu_t) = (\mathbf{P}_t^*)'(\mu_t + MG_S)$ is the resulting firm distribution after endogenous entry-exit decisions. $\mathbf{P}_t^*$ is a transition matrix which summarizes the endogenous entry-exit results. The rows of this matrix are zeros up to a certain cutoff threshold $S^*(w_t(\mu_t))$. This can be viewed as the deterministic component resulting from optimal entry-exit decisions.

There are also shocks to the firm distribution, ϵ_{t+1}, with $E[\epsilon_{t+1}] = \mathbf{0}$, and a variance-covariance matrix $\Sigma(\mu_t) = \sum_{s=s^*(\mu_t)}^{S}(MG_S + \mu_{s,t})(\text{diag}(P_{s,}) - P_{s,}'P_{s,})$, where $P_{s,}$ is the transition matrix with rows of zeroes for productivity levels below the cutoff threshold. We generate 5,000 independent draws of firm distribution shocks, discard the first 1,000 draws, and calculate standard deviations of the growth rates of the aggregates quantities and real wages. Table 2 summarizes the simulated results and compares them with the data.

Table 2: Business Cycle Characteristics

	Japan		U.S. (CG (2016))	
	Model	Data	Model	Data
Real output (Y)	1.502	1.640	0.47	1.83
Labor supply (L)	1.002	0.918	0.31	1.78
TFP (A)	0.888	0.809	0.21	1.04
Real wage (w)	0.501	0.803	–	–

Note: Numbers for Japan represent standard deviations of detrended annual growth rates in percent. The observation period for Japan is from 1976 to 2014.

The business cycle statistics of the calibrated model for Japan are close to those of the data. Real output is the most volatile among the aggregate quantities, followed by labor supply, TFP, and real wages. The U.S. results from Carvalho and Grassi (2016) are also shown for reference. These results are consistent with the insights from Canals et al. (2007) and di Giovanni and Levchenko (2012), who point out that in granular economies, where large firms make up a major proportion of, for example, exports, shocks to the upper tail of the firm distribution play an important role in driving aggregate fluctuations. Not only is the CG model simple and tractable, we believe it also provides a good description of the Japanese economy, replicating the business cycle well.

3.2 Large Firm Shocks and Net Entry

We demonstrate the quantitative impact of an idiosyncratic shock to the largest firm using our calibrated model for Japan. Specifically, we will refer to large-firm shocks as shocks to the upper tail of the firm size distribution. Figure 2 shows the impulse response of aggregate output to a negative 15 percent technology shock to the largest firm. For comparison, the same shock to an average-sized firm is also considered. When the largest firm is hit by the negative shock, this has a substantial macroeconomic impact, whereas the macroeconomic impact of the same negative shock to an average-sized firm is negligible. The mechanism works as follows: the negative shock to the largest firm drives down real wages and results in excess profits for other firms. This induces other firms to ramp up their production; however, due to decreasing returns to scale, they cannot sufficiently increase production to compensate for the negative shock. As a result, shocks to large firms have a macroeconomic impact.

From equations (1) and (2), we can see that the evolution of aggregate productivity will depend not only on shocks to the firm distribution but also on the net-entry term. In the CG model, potential entrants follow an exogenous Pareto distribution, but when we think of the exogenous entry of a highly productive firm of a massive size, this will also have a macroeconomic impact, as in the above exercise.

Overall, these results and insights from Carvalho and Grassi (2016) indicate that idiosyncratic shocks to large firms as well as net entry are important sources of productivity fluctuations in Japan and the U.S.

3.3 Thicker Tails in the Firm Distribution

What does the model imply when the distribution of potential entrants gets thicker in the tails? Figure 3 compares impulse responses with different tail parameters (δ_e, and δ) for the firm distribution. When the tails of the distribution get thicker, the impact of large firm shocks becomes larger. This is intuitive, since thicker tails imply larger firms in the tails.

Further, Figure 4 shows the entry rates with different tail parameters. We define the entry rate in terms of the ratio of entering firms' output to total output. Our results shows that as the tail of the distribution gets thicker, the entry rate declines.[10] This is a natural outcome since when δ is larger than one, the expectation of the pareto distribution ($E(x) = \frac{\delta}{\delta-1}$) is a decreasing function with respect to δ. Hence, when the firm distribution becomes more fat tailed, the value of entry will be lower and this could depress entry motives of potential entrants and lead to declines in the entry rate.

4 Empirical Analysis

The previous section utilized the CG model to show that idiosyncratic shocks to large firms and net entry have a macroeconomic impact and are key sources of business cycle fluctuations. In this section, we empirically investigate how the various aspects of large firm dynamics, i.e., idiosyncratic shocks to large firms, firm entry and exit, and realloca-

[10] The figure shows that the entry rate declines in a stepwise fashion. This is due to the discretization of the productivity space, and when the entry threshold rises with lower tail parameters, there is a discrete jump in the entry rate.

tion have contributed to productivity growth in Japan and the U.S. We proceed by first analyzing the role of entry, exit, and reallocation using the dynamic Olley–Pakes method proposed by Melitz and Polanec (2015) to see how the business dynamics of large firms affected productivity growth. Second, we will run granular regressions following Gabaix (2011) to see how idiosyncratic shocks to large firms lead to aggregate productivity fluctuations. Third, we decompose the granular residual into the contribution of individual firms and aggregate them into sectors to examine which sectors played a major role in determining productivity trends.

4.1 Data

Firm-level data for Japan are obtained from the *Nikkei NEEDS-Financial Quest* database, which covers publicly listed companies. First, we obtain the nominal annual sales series for each firm and convert these series into real terms using sectoral output deflators from the SNA.[11] We map the 132 industry classifications in the database to the 23 sector classification of the SNA. The number of employees for each firm is also obtained from the Nikkei NEEDS database, and we use this to calculate firm-level labor productivity by dividing real sales by the number of employees.[12] The main advantage of using the Nikkei database is that we are able to obtain not only data for existing firms — as of today — but also data for exiters as well. This enables us to analyze the quantitative impact of entry, exit, and reallocation effects. The database covers firms listed on the first and second sections of the Tokyo Stock Exchange, on JASDAQ and Mothers, as well

[11] For some firms, observations for some data points are missing, so that we use linear interpolation in the sales and employees series to calculate firm-level labor productivity. Note also that the sales and employees data for each firm are based on consolidated accounts which includes overseas sales for multinationals.

[12] Labor productivity of firm i is defined as $A_{i,t} = (P_{i,t}X_{i,t})/(P^S_{i,t}L_{i,t})$, where the total nominal sales of firm i, $P_{i,t}X_{i,t}$, are divided by firm i's sector's output deflator, $P^S_{i,t}$, and the number of employees, $L_{i,t}$. Individual prices $P_{i,t}$ and quantities $X_{i,t}$ are unobservable, but since we have greatly disaggregated output deflators, we proceed by assuming that the difference between inflation in individual prices and the sector prcie are small, so that labor productivity growth rates $g_{i,t} = g^{X/L}_{i,t} + (\pi_{i,t} - \pi^S_{i,t})$ can be treated as real terms.

as the Nagoya and Osaka stock exchanges. The total number of firms amounts to 5,378 in total. When aggregating firm-level data into sector groups, we use Nikkei's industry classification, which is more detailed than other industry-level data. Following Gabaix (2011), we exclude energy companies; in addition, we also exclude trading companies, since their sales, productivity, etc., are greatly influenced by fluctuations in commodity prices. The observation period for Japan is from 1965 to 2014. Labor productivity at the macro level is calculated using real GDP from the SNA and number of employees data from the Ministry of Health, Labour and Welfare. The data for TFP are based on Bank of Japan estimates. The construction of data for the U.S. is similar to the construction of data for Japan and the procedures in Gabaix (2011). Firm-level data for the U.S. are obtained from *Compustat*, while other macroeconomic variables are obtained from the Bureau of Economic Analysis. TFP series are multifactor productivity series for private business obtained from the Bureau of Labor Statistics.

4.2 Dynamic Olley–Pakes Decomposition

Recall from equation (1) that net entry was a determinant of aggregate productivity. Gordon (2012, 2015) has expressed concern from the supply-side perspective that a decline in business dynamism has put negative pressure on productivity growth. The goal of this section is to see how the business dynamics of large firms — entry, exit, and reallocation — have contributed to productivity growth. As documented in Foster, Haltiwanger, and Krizan (2001), net entry spurs productivity growth. We analyze the contributions from entry and exit as proxies for business dynamics, using the dynamic Olley–Pakes productivity decomposition — hereafter, DOP decomposition — recently proposed by Melitz and Polanec (2015).[13] The main feature of this method is that the decomposition is conducted based on the moments of the productivity and market share distributions. There

[13] A recent paper by Decker et al. (2017) also uses DOP decomposition on firm-level data in the U.S. and shows that a decline in allocative efficiency accounted for the bulk of the productivity slowdown from the late 1990s to the mid-2000s.

are other decomposition methods of aggregate labor productivity at the firm level, such as those proposed by Griliches and Regev (1995) and Foster, Haltiwanger, and Krizan (2001). However, Melitz and Polanec (2015) report that DOP decomposition is effective for eliminating biases in the measurement of the contribution of entry and exit found in other decompositions. For this reason, we use DOP decomposition.

The outline of the DOP decomposition is as follows. We first decompose firms in a certain time period — say time t — into three groups: entrants, exiters, and surviving firms. Entrants are defined as firms that were not present in the previous period and entered the economy at time t.[14] Likewise, exiters are firms that were present until the previous period but left the economy in period t. Surviving firms are firms that were present in both periods. Second, we merge these groups to calculate aggregate productivity. Denoting the weighted average labor productivity in a certain group G as $\Phi_t^G = \sum_{i \in G} s_{i,t}\varphi_{i,t}$, the aggregate productivity level — in log levels — in period t and $t-1$ can be written as

$$\Phi_t = S_t^S \Phi_t^S + S_t^E \Phi_t^E = \Phi_t^S + S_t^E(\Phi_t^E - \Phi_t^S),$$

$$\Phi_{t-1} = S_{t-1}^S \Phi_{t-1}^S + S_{t-1}^X \Phi_{t-1}^X = \Phi_{t-1}^S + S_{t-1}^X(\Phi_{t-1}^X - \Phi_{t-1}^S),$$

where S_t^G denotes the share of group G in total sales. Taking the difference of these two expressions corresponds to the growth rate of aggregate labor productivity. After some rearrangement, this can be expressed as

$$\Delta\Phi_t = \Delta\tilde{\varphi}_t^S + \Delta\text{cov}(s, \varphi) + S_t^E(\Phi_t^E - \Phi_t^S) + S_{t-1}^X(\Phi_{t-1}^S - \Phi_{t-1}^X).$$

Therefore, the growth rate of aggregate labor productivity is decomposed into four com-

[14] As documented in many empirical studies — such as Foster, Haltiwanger, and Krizan (2001) —, entrants tend to grow faster than other firms. To capture this profile, we treat firms as entrants up to three years after their entry.

ponents: the average growth of surviving firms, $\Delta\tilde{\varphi}_t^S$, the change in the covariance of the shares and productivity of surviving firms, $\Delta\text{cov}(s,\varphi)$ — which we call the reallocation effect —, and the contribution of firm entry and exit. In other words, the reallocation effect relates individual firms' productivity and their market share. When the share of a highly productive firm increases, the aggregate productivity level increases, and vice versa.

Figures 5 and 6 show the DOP decomposition of labor productivity for Japan and the U.S. The result for Japan is presented in Figure 5 and shows some notable features. First, even though they are based on different statistical sources, developments in labor productivity constructed from firm-level data closely resemble those calculated from aggregate data. Second, although firm entry made a positive contribution to productivity growth from the early 2000s until the mid-2000s, the contribution of net entry is rather small in Japan compared to the U.S. In fact, most of the contribution of firm entry comes from the top 20 entrants ordered by size.[15] Further, this finding supports the granular hypothesis that large firms matter for net entry as well. Third, following the Great Recession, the positive contribution of entry has dissipated and sales weights have shifted towards firms with lower productivity, indicating that reallocation effects have put downward pressure on labor productivity growth.

The results for the U.S. in Figure 6 paint a picture of more active firm dynamics than in Japan. First, as in Japan, developments in firm-level labor productivity that we constructed closely resemble those calculated from aggregate data. One of the major factors driving the productivity slowdown from the 1990s is the reallocation effect. The contribution of the entry effect was positive throughout most of the period but has declined since the mid-2000s. This is in line with Gordon's (2012, 2015) findings, which suggest that a cause of the secular stagnation was a decline in business dynamism that

[15] The correlation between the contribution of the top 20 entrants and total entrants is 0.96 for Japan and 0.91 for the U.S. The top 20 entrants on average correspond to the top 6 percentile of overall entrants in Japan and the top 1.8 percentile in the U.S.

contributed to slower productivity growth. To see this in more detail, Figure 7(a) decomposes the contribution of firm entry into the contributions of two groups of firms: U.S. firms and foreign firms entering the U.S.[16] The figure allows a number of observations. First, we can see that the 1960s to the mid-1970s were a golden age for U.S. firms, where new entry of domestic firms made a positive contribution to aggregate productivity growth. These firms were the foundation for high growth in later periods. Second, most of the positive contribution from the 1990s to the mid-2000s was made by foreign firms entering the U.S. A detailed breakdown of foreign firms entering the U.S. by sector is shown in figure 7(b), where we see that the high contribution of firm entry during this period was mainly driven by entries in the broadcasting and telecommunications sector. As shown by Fernald (2015), this can be viewed as the fruits of the IT revolution reflecting the high degree of business dynamism, since many foreign firms entered the U.S. during this period to improve their communication networks. Recent developments since the Great Depression show some signs of a pick up as more entries of domestic firms into the stock market — for example of social network firms such as Facebook in 2012 — can be observed, but the contribution of foreign firms has dissipated, which has reduced economic metabolism. Between the late 1990s and the mid-2000s, the contribution of exiters was negative, but this was mainly due to the effects of large mergers and acquisitions (M&As), in which exiters merged with or were acquired by existing firms or new entrants. In sum, our DOP decomposition is consistent with the supply-side view that a decline in business dynamics since the mid-2000s has depressed productivity growth in the U.S.

4.3 Granular Regressions with Entry, Exit, and Reallocation

In the previous section, we examined how business dynamics — i.e., entry, exit, and reallocation — contribute to aggregate productivity growth. In this section we quantitatively

[16] We use FIC and LOC codes to classify U.S. firms and foreign firms based in the U.S.

assess the impact of idiosyncratic shocks to large firms, following Gabaix (2011).

We work with granular regressions, in which we regress fluctuations in productivity growth on proxies of idiosyncratic large-firm shocks such as the granular residuals. Gabaix (2011) shows that the granular residual performs well in explaining aggregate fluctuations and TFP growth in the U.S. This seminal finding provides evidence that idiosyncratic shocks to large firms are key origins of aggregate fluctuations. This is consistent with the theoretical predictions in Sections 2 and 3, where we showed that large-firm shocks result in aggregate fluctuations.

In this section, we perform granular regressions in the spirit of Gabaix (2011), adding the contributions of entry, exit, and reallocation from the DOP decomposition to the explanatory variables. To start with, using the top 100 firms in terms of size, we define the granular residual Γ_t as

$$\Gamma_t = \sum_{i=1}^{100} \frac{S_{i,t-1}}{Y_{t-1}} (g_{i,t} - \bar{g}_t),$$

where $S_{i,t-1}$, Y_{t-1}, $g_{i,t}$, and $\bar{g}_t$ denote the real sales of firm i, real GDP, the growth of labor productivity of firm i, and the average productivity growth of all firms, respectively. Recall that all variables are in real terms, and weights of the idiosyncratic shock $S_{i,t-1}/Y_{t-1}$ are fixed in the previous period, so there are no reallocation effects. We use this measure as a proxy for idiosyncratic shocks to large firms.

Combining equation (1) and (2), we can express productivity fluctuations with idiosyncratic shocks to large firms, as well as net entry terms. We use the above granular residual along with the contributions of entry, exit, and reallocation from the previous section — denoted by Z_t — and perform granular regressions of the following form:

$$g_t^{prod} = c + \beta(L)\Gamma_t(L) + \gamma Z_t + \epsilon_t, \tag{3}$$

where g_t^{prod} is the productivity growth rate, $\Gamma_t(L)$ includes contemporaneous and lagged granular residuals, and ϵ_t are error terms. We will use labor productivity growth and

TFP growth for g_t^{prod}. The results of these regressions are summarized in Table 3. The overall fit for Japan and the U.S. is quite good and the model explains about 30 to 40 percent of the overall fluctuations in aggregate labor productivity and TFP. The granular residual is significant in all specifications. In terms of the proxies of business dynamics — i.e., entry, exit, and reallocation — net entry is significant for the U.S. but not for Japan. This is in line with the observations from the previous section that the entry and exit of large firms makes a substantial contribution to productivity growth in the U.S. but not in Japan. Meanwhile, reallocation effects are significant for both countries.

4.4 Estimating Sectoral Contributions to Productivity Growth Using Granular Regressions

We can use the granular regression approach to investigate in a bottom-up manner which sectors, or firms play a dominant role in determining aggregate productivity fluctuations. In other words, granular regression can be used as a way to identify the determinants of productivity growth. This enables us to examine questions such as which firms or sectors contributed to the high productivity growth observed in Japan during the 1980s or were responsible for the recent productivity slowdown in the U.S. In our analysis, we will aggregate firm-level contributions into sectors based on the Nikkei sector classification for Japan and the SIC sector classification for the U.S.

Recall that the granular residual is constructed as the weighted average of the excess productivity growth of the top 100 firms in terms of size. We trace individual firm's contribution to aggregate productivity $\hat{c}_{i,t}$ using the estimated parameters from equation (1). $\hat{c}_{i,t}$ is calculated as follows:

$$\hat{c}_{i,t} = \hat{\beta}(L)\frac{S_{i,t-1}(L)}{Y_{t-1}(L)}(g_{i,t}(L) - \bar{g}_t(L)).$$

We aggregate these contributions into individual sectors to see which sectors play a major role in determining aggregate TFP fluctuations. Figure 8 shows the historical contribution of each sector to aggregate TFP growth in Japan and Table 4 shows the top and bottom 5 firms which had contributed to TFP growth. The figure indicates, first, that throughout the observation period, a limited range of sectors were the main drivers of TFP growth, namely, transport equipment, electronic components and devices, and information technology sectors. Second, the high growth in the 1980s was driven largely by firms in transport equipment — mainly consisting of firms such as Toyota, Nissan, and Honda — and electronic components and devices sectors — mainly consisting of Hitachi, Toshiba and Panasonic —. Third, however, in recent years, the contribution of the electronics components and devices sector has registered a sharp decline. This decline can be pinned down to more detailed segments within the sector, as shown in Figure 9. The figure and Table 4 indicates that the recent decline is mainly driven by firms in the general electronics and household electronics segments — firms such as Toshiba, Hitachi, Sharp and NEC etc —. For example, the sharp decline in the contribution to overall TFP growth of general electronic companies since 2011 can be interpreted as adverse shocks at the time of the Great Eastern Japan Earthquake in 2011, where some firms may have revised their long-term business plans related to the building of nuclear power plants, which will have an effect on the long-run trend of sales. The recent decline in the TFP growth contribution of the household electronics sector potentially reflects greater competition from rival firms abroad, whose technology has started to catch up with Japanese firms in this segment.

Overall, our results are consistent with those obtained by Fukao et al. (2004), who show that manufacturing sectors were the primary sources of the decline in productivity growth from the 1980s to the 1990s. However, we did not detect any evidence of high productivity growth in the non-manufacturing sector in the 1990s, which was one of the main findings of Fukao et al. (2004). This difference may be due to the fact that we excluded trading companies, whose sales are greatly affected by fluctuations in commodity prices, and small firms.

Figure 10 shows the contribution of individual sectors to overall TFP growth in the U.S. As can be seen, the sectors that historically have made the greatest contribution are the durable goods and information technology sectors. Table 5 shows the the top and bottom 5 firms which had contributed to TFP growth, and we can see that among these sectors, firms such as General Motors and AT&T were most influential. Weak developments since the Great Recession have been a rather wide-spread phenomenon: although growth in the information technology sector — which consists of domestic IT firms — and retail trade has regained the pace of the late 1990s, weakness is observed not only in the durable goods sector, especially in firms such as General Motors, Ford etc., but also in the nondurable goods and wholesale trade sectors. We can confirm this observation from from Table 5, where we see weakness in for example Walmart, and Amazon reflecting weak domestic demand following the financial crisis. To examine developments in the durable goods sector in more detail, Figure 11 provides a breakdown into segments. The figure indicates that historical developments are driven mostly by the motor vehicles, bodies and trailers, and parts industry, which includes firms such as General Motors, Ford, Chrysler etc.

5 Identification of Demand and Supply Shocks and Their Effects on Productivity Fluctuations

The aim of this section is to derive implications for the secular stagnation debate by identifying demand and supply shocks using the granular residual and sectoral inflation rates to examine their effects on productivity.

5.1 Identification Using the Granular Residual

We identify demand and supply shocks by matching idiosyncratic firm-level shocks with changes in sectoral inflation rates. Using changes in sectoral inflation rates will eliminate intrasectoral differences in the level of inflation rates. For example, an idiosyncratic shock to Toyota is matched with the change in the inflation rate of the automobile sector of that year. When identifying demand and supply shocks, most of the existing literature on secular stagnation uses aggregate inflation for identification, but we prefer using micro-level data for identification on several grounds. Summers (2015, 2016) refers to the decline in aggregate inflation and concludes that demand shocks were the major source of the Great Recession and low growth. However, following the Great Recession, it is also true that inflation rates did not decline as anticipated, which has been referred to as "the missing disinflation" phenomenon (Hall, 2011). This suggests that deflationary pressures due to negative demand shocks were offset by negative supply shocks. Furthermore, the propagation of shocks could differ depending on the underlying type of shock; that is, there could be differences in the way demand and supply shocks affect productivity. Overall, we believe identification based on aggregate inflation is not sufficient and a more detailed analysis at the disaggregated level is necessary to determine how demand and supply shocks affect productivity.

The basic idea underlying our identification strategy is straightforward: when quantity and inflation move in the same direction simultaneously, this is considered as a demand shock, and when quantity and inflation move in opposite directions, this is considered as a supply shock. Since we are measuring labor productivity using firms' sales data, fluctuations could be influenced by both demand and supply factors. Demand shocks to large firms may include, for example, exogenous shocks stemming from developments in overseas economies. When there is a positive shock to overseas economies, large exporters will experience a surge in demand, and if increases in input — such as labor — are slower than increases in output, this will result in productivity gains. Ultimately, excess demand will drive up prices, so that productivity and prices will move in the same direction. On the other hand, supply shocks can be viewed as, for example, innovations within firms or efficiency gains from overseas production of large firms. These innovations lower the marginal cost of production, which puts downward pressure on sales prices. In this case, productivity and prices move in opposite directions. In order to examine the relation between idiosyncratic large firm shocks and inflation across sectors, we use changes in sectoral inflation rates to eliminate intrasectoral differences in the level of inflation rates. We therefore divide the 100 firms that are included in the granular residual into two groups $i \in \{1, 2, ..., N\}$, namely, those that experienced a demand shock and those that experienced a supply shock:

$$D_t = \{(\tilde{g}_{i,t}, \Delta\pi_{i,t}) | \{\tilde{g}_{i,t} > 0 \wedge \Delta\pi_{i,t} > 0\} \cup \{\tilde{g}_{i,t} < 0 \wedge \Delta\pi_{i,t} < 0\}\},$$

$$S_t = \{(\tilde{g}_{i,t}, \Delta\pi_{i,t}) | \{\tilde{g}_{i,t} > 0 \wedge \Delta\pi_{i,t} < 0\} \cup \{\tilde{g}_{i,t} < 0 \wedge \Delta\pi_{i,t} > 0\}\},$$

where $\tilde{g}_{i,t} \equiv g_{i,t} - \bar{g}_t$ is the idiosyncratic shock to the large firm, and $\Delta\pi_{i,t}$ is the change in the matched sectoral inflation rates. We sum the contributions of individual firms in the granular residual over these sets to form granular demand and supply shocks, i.e.:

$$\Gamma_t^X = \sum_{i \in X} \frac{S_{i,t-1}}{Y_{t-1}} (\tilde{g}_{i,t}), X \in \{D, S\}.$$

To illustrate our approach, Figure 12 shows the identification of supply shocks for Japan in 2008. The horizontal axis represents the contribution to aggregate TFP growth obtained from the regression using equation (3), which measures the impact of idiosyncratic shocks to large firms and the vertical axis represents changes in the matched sectoral inflation rates. A granular demand shock at a certain point in time corresponds to the sum of each granular contribution in the first and third quadrants of this plane; likewise, a granular supply shock correspond to the sum of all points in the second and fourth quadrants. As mentioned in Section 4.1, we transformed the sales of firm i into real terms by dividing nominal sales by firm i's sector's output deflator. Since sectors are greatly disaggregated, we assume that the inflation differentials between individual prices and sectoral prices are sufficiently small to ignore them, so there will be no systematic correlation between the change in the sector's inflation rate and idiosyncratic shocks to large firms. Note also that the identification scheme would not work if firms were concentrated in one of the two regions, or displayed some systematic patterns associated with business cycles. To check this point, Figure 13 presents the share of firms for Japan and the U.S. that experienced demand shocks and we can see that this share is fairly stable around 50 percent throughout the observation period, which indicates that firms are evenly distributed over this plane and do not follow systematic patterns.

5.2 Granular Regressions with Demand and Supply Shocks

As in Section 4.3, we regress productivity growth on identified granular demand (Γ_t^D) and supply (Γ_t^S) shocks, controlling for entry, exit, and reallocation (Z_t). The regression takes the following form:

$$g_t^{prod} = c + \beta^D(L)\Gamma_t^D(L) + \beta^S(L)\Gamma_t^S(L) + \gamma Z_t + \epsilon_t. \tag{4}$$

Figures 14 and 15 show the contributions of demand and supply shocks to TFP growth in Japan and the U.S. The dotted line in each figure shows the five-year moving average. A closer look at the developments in Japan shows that the high productivity growth in the 1980s was mostly driven by supply shocks rather than demand shocks. This observation supplements the sectoral analysis using granular regressions in the previous section, where we highlighted that transport equipment, electronic components and devices, and information technology industries were the primary sources of high productivity growth in the 1980s. These findings suggest that the TFP growth of firms in these sectors was driven mainly by supply shocks. Developments in the U.S. show that supply shocks had positive effects in the early 2000s, but these effects have declined since the mid-2000s. This result is in line with Fernald's (2015) findings, who documented that the fruits of the information technology revolution had already reaped by the mid-2000s and their role has declined since then. Meanwhile, demand shocks were the major source of the Great Recession, which is in line with Summers' (2015, 2016) argument, but these shocks were offset by positive demand shocks in subsequent years. These observations suggest that the declining trend in productivity growth in both countries has been driven by mostly supply shocks rather than demand shocks.

5.3 Local Projections

In order to examine if there are differences in how productivity responds to demand and supply shocks, we use the local projection method (LPM) developed by Jordà (2005) for equations (3) and (4). Figure 16 shows the LPM cumulative impulse responses of TFP to granular residual shocks for Japan and the U.S. The left panel for each country depicts the LPM results using equation (3), while the middle and right panels depict the results from equation (4). The lag in the local projections is set to 1 based on the Schwarz information criterion. For comparison, impulse responses based on vector autoregressions (VARs) are also shown in each figure. As can been seen, the results from the VARs are similar to those obtained based on the LPM. The results for both countries share similar characteristics in that granular residual shocks have a positive effect on productivity, and while the effect of demand shocks ($\Gamma_t^D(L)$) is short lived, supply shocks ($\Gamma_t^S(L)$) have a permanent effect on productivity. This result closely resembles the long-run identification scheme of Blanchard and Quah (1989), who assumed that supply shocks have long-run effects on output, whereas demand shocks only have short-run effects.

Overall, our empirical results support the view expressed by Gordon (2012, 2015, 2016) and Fernald (2015), who suggest that the productivity slowdown — i.e., the secular stagnation phenomenon — is mainly driven by supply shocks rather than demand shocks.

6 Conclusion

To examine the recently discussed secular stagnation phenomenon, we focused on the role of large firm dynamics as determinants of productivity growth. Our simulation exercise using the Carvalho and Grassi (2016) model supports Gabaix's (2011) granular hypothesis that idiosyncratic shocks to large firms have an impact on the macroeconomy. Using firm-level data for Japan and the U.S., we empirically showed that idiosyncratic shocks to large firms as well as entry, exit, and reallocation effects account for 30 to 40 percent of productivity fluctuations in both countries. This is also in line with the granular hypothesis and shows that large firm dynamics are a key source of aggregate fluctuations. In terms of the effects of business dynamics, we find that in Japan net entry makes a small contribution to productivity growth, which contrasts with the situation in the U.S. We also find that the IT revolution led many foreign firms to enter the U.S. during the late 1990s to the mid-2000s, which made a positive contribution to productivity growth. However, since the Great Recession, slower entry of foreign firms has led to a decline in business dynamism and to downward pressure on productivity growth. In order to identify demand and supply shocks, we utilized individual contributions from the granular residual and changes in the matched sectoral inflation rates. Our granular regressions showed that the prolonged productivity slowdown in Japan and the U.S. was mostly driven by supply shocks, while impulse responses from local projections show that supply shocks have permanent effects on productivity, whereas demand shocks only have short run effects. Overall, these findings support the supply-side views of Gordon (2012, 2015, 2016) in the secular stagnation debate.

Our analyses rely heavily on the granular hypothesis and do not consider the role of small firms. The reason for this omission is the prediction that idiosyncratic shocks to small firms are likely to be compensated for by other firms of the same size and therefore have no impact on aggregate fluctuations. Furthermore, small firms form part of the production chains of large firms and may also be affected by idiosyncratic shocks to large firms, which are located at the end of the production chains. That being said, the sales share of small firms amounts to a non-negligible fraction of the whole economy, so that it would be interesting to see how small-firm business dynamics as well as production chains have affected productivity growth. Another line of potential research related to our findings concerns the impact of large M&As on productivity growth. Our DOP decompositions showed that exiters made a negative contribution to productivity growth. The reason for this negative exit effect likely is that exiters were high-productivity firms that were merged with or acquired by new entrants or existing firms. Building economic models that incorporate M&As as well as more in-depth analyses on the role of M&As provide an avenue for future research to shed more light on the link between business dynamics and secular stagnation.

References

Acemoglu, D., Carvalho, V.M., Ozdaglar, A., and Tahbaz-Salehi, A. 2012. "The Network Origins of Aggregate Fluctuations," *Econometrica*, 80(5): 1977–2016.

Axtell, R.L. 2001. "Zipf Distribution of US Firm Sizes," *Science*, 293(5536): 1818–1820.

Bernanke, B.B. 2015. "Why Are Interest Rates So Low, Part 3: The Global Savings Glut," http://www.brookings.edu/blog/ben-bernanke/2015/04/01/why-are-interest-rates-so-low-part-3-the-global-savings-glut/.

Blanchard, O.J., Cerutti, E., and Summers, L.H. 2015. "Inflation and Activity - Two Explorations and their Monetary Policy Implications," IMF Working Paper Series, WP/15/230.

Blanchard, O.J., and Summers, L.H. 1986. "Hysterisis and the European Unemployment Problem," *NBER Macroeconomics Annual 1986*, 1: 15–90.

Blanchard, O.J., and Quah, D. 1989. "The Dynamic Effects of Aggregate Demand and Supply Disturbances," *American Economic Review*, 79(4): 655–673.

Byrne, D., Fernald, J.C., and Reinsdorf M.B. 2016. "Does the United States Have a Productivity Slowdown or a Measurement Problem," *Brookings Papers on Economic Activity*, Spring 2016: 109–182.

Canals, C., Gabaix, X., Vilarrubia,J.M., and Weinstein, D.E. 2007. "Trade Patterns, Trade Balances, and Idiosyncratic Shocks," Banco de Espana Working Paper no. 02/2007, la Caixa, Barcelona.

Carvalho, V.M., and Gabaix, X. 2013. "The Great Diversification and Its Undoing," *American Economic Review*, 103(5): 1697–1727.

Carvalho, V., Grassi, B. 2016. "Large Firm Dynamics and the Business Cycle," Cambridge Working Papers in Economics 1556.

Clementi, G.L., and Palazzo B. 2016. "Entry, Exit, Firm Dynamics and Aggregate Fluctuations," *American Economic Journal: Macroeconomics* , 8(3): 1–41.

Decker, R.A., Haltiwanger, J., Jarmin, R.S., and Miranda, J. 2017. "Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown," Federal Reserve Board Finance and Economics Discussion Series, 019–2017.

di Giovanni, J., and Levchenko, A.A. 2012. "Country Size, International Trade, and Aggregate Fluctuations in Granular Economies," *Journal of Political Economy*, 120(6): 1083–1132.

di Giovanni, J., Levchenko, A.A., and Mejean, I. 2014. "Firms, Destinations, and Aggregate Fluctuations," *Econometrica*, 82(4): 1303–1340.

Fernald, J. 2015. "Productivity and Potential Output Before, During, and After the Great Recession," *NBER Macroeconomics Annual 2015*, 29: 1–51.

Foster, L., Haltiwanger, J.C., and Krizan, C.J. 2001. "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," In C.R. Hulten, E.R. Fean, and M.J. Harper, eds., *New Developments in Productivity Analysis.* Chicago: University of Chicago Press.

Fukao. K., Inui, T., Kawai, H., and Miyagawa, T. 2004. "Sectoral Productivity and Economic Growth in Japan, 1970-98: An Empirical Analysis Based on the JIP Database," published in *Growth and Productivity in East Asia, NBER-East Asia Seminar on Economics*, 13: 177–227.

Gali, J. 1999. "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?," *American Economic Review*, 89(1): 249–271.

Gali, J., and Rabanal, P. 2004. "Technology Shocks and Aggregate Fluctuations: How Well Does the Real Business Cycle Model Fit Postwar U.S. Data?," *NBER Macroeconomics Annual 2004*, 19: 225–288.

Gabaix, X. 2011. "The Granular Origins of Aggregate Fluctuations," *Econometrica*, 79(3): 733–772.

Gordon, R.J. 2012. "Is U.S. Economic Growth Over? Faltering Innovation Confronts the Six Headwinds," *NBER Working Paper Series*, No. 18315.

———, 2015. "Secular Stagnation: A Supply-Side View," *American Economic Review: Paper & Proceedings*, 105(5): 54–59.

———, 2016. "Perspectives on The Rise and Fall of American Growth," *American Economic Review: Paper & Proceedings*, 106(5): 1-7.

Griliches, Z. and Regev, H. 1995. "Firm Productivity in Israeli Industry: 1979–1988," *Journal of Econometrics*, 65: 175–203.

Hall, R.E. 2011. "The Long Slump," *American Economic Review*, 101: 431–469.

Hansen, A.H. 1939. "Economic Progress and Declining Population Growth," *American Economic Review*, 29(1): 1–15.

Hayashi, F. and Prescott, C.E. 2002. "The 1990s in Japan: A Lost Decade," *Review of Economic Dynamics*, 5(1): 206-235.

Hopenhayn, H.A. 1992. "Entry, Exit, and Firm Dynamics in Long Run Equilibrium," *Econometrica*, 60(5): 1127–1150.

Jordà, Ò. 2005. "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95: 161–182.

Jorgenson, D.W., and Motohashi, K. 2005. "Information Technology and the Japanese Economy," *Journal of the Japanese and International Economies*, 19(4): 460–481.

Jorgenson, D.W., and Nomura, K. 2007. "The Industry Origins of the US-Japan Productivity Gap," *Economic Systems Research*, 19(3): 315–341.

Kawamoto, T. 2005. "What Do the Purified Solow Residual Tell Us About Japan's Lost Decade?," *Monetary and Economic Studies*, February 2005: 113–148.

Krugman, P. 2013. "Secular Stagnation, Coalmines, Bubbles, and Larry Summers," *The New York Times*, November 16, 2013.

Lo, S., and Rogoff, K. 2015. "Secular Stagnation, Debt Overhang and Other Rationales for Sluggish Growth, Six Years On," *BIS Working Papers*, No. 482.

Melitz, J. M. and Polanec S. 2015. "Dynamic Olley-Pakes Productivity Decomposition with Entry and Exit," *RAND Journal of Economics*, 46(2): 362–375.

Summers, H. L. 2014. "Reflections on the 'New Secular Stagnation Hypothesis'." In *Secular Stagnation: Facts, Causes, and Cures,* edited by Teulings, C., and Baldwin, R., 27–40. London: CEPR Press.

——— , 2015. "Demand Side Secular Stagnation," *American Economic Review: Paper & Proceedings*, 105(5): 60–65.

——— , 2016. "Crisis in Economic Thought, Secular Stagnation, and Future Economic Research," *NBER Macroeconomics Annual 2016*, 31: 557–577.

Teulings, C., and Baldwin, R. 2014. "Secular Stagnation: Facts, Causes, and Cures," London: CEPR Press.

Figure 1: Steady State Firm Distribution

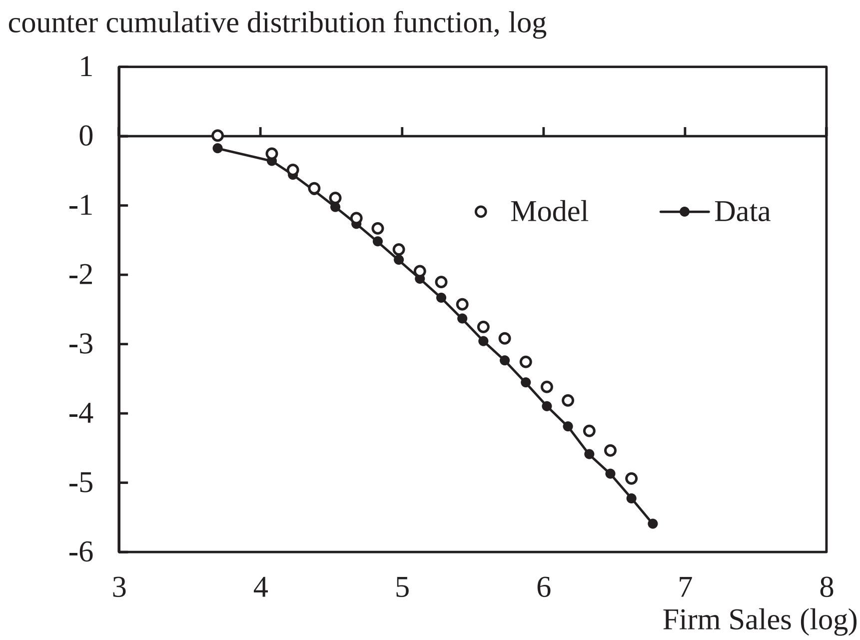


Figure 2: Impulse Response of Aggregate Output to a Negative 15% Productivity Shock to Idiosyncratic Productivity

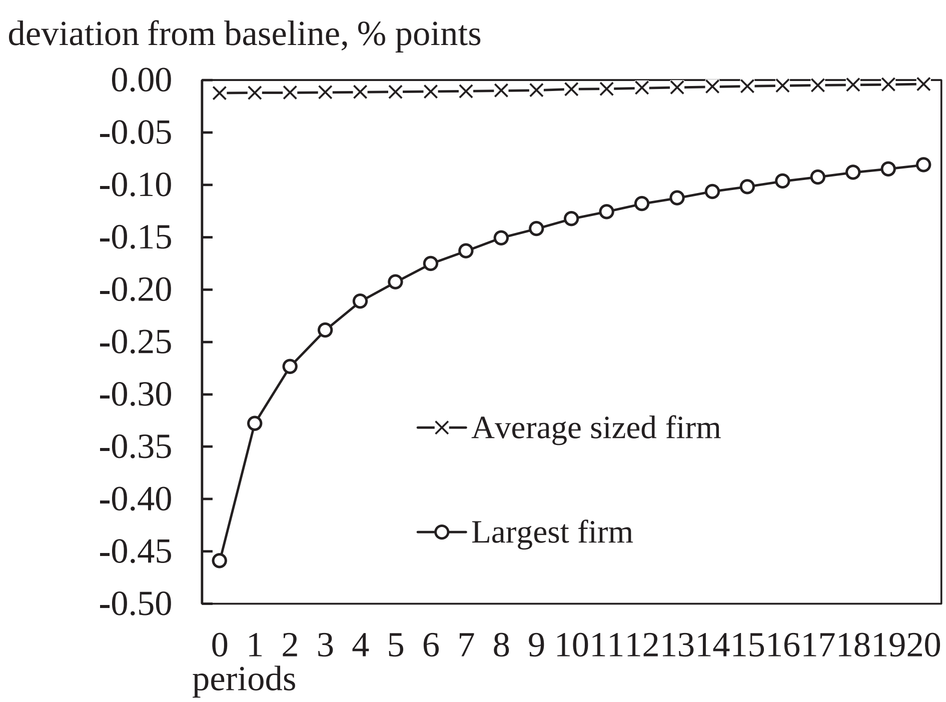


Figure 3: Comparison of Impulse Responses of Aggregate Output to a Negative 15% Productivity Shock to the Largest Firm with Different Tail Parameters

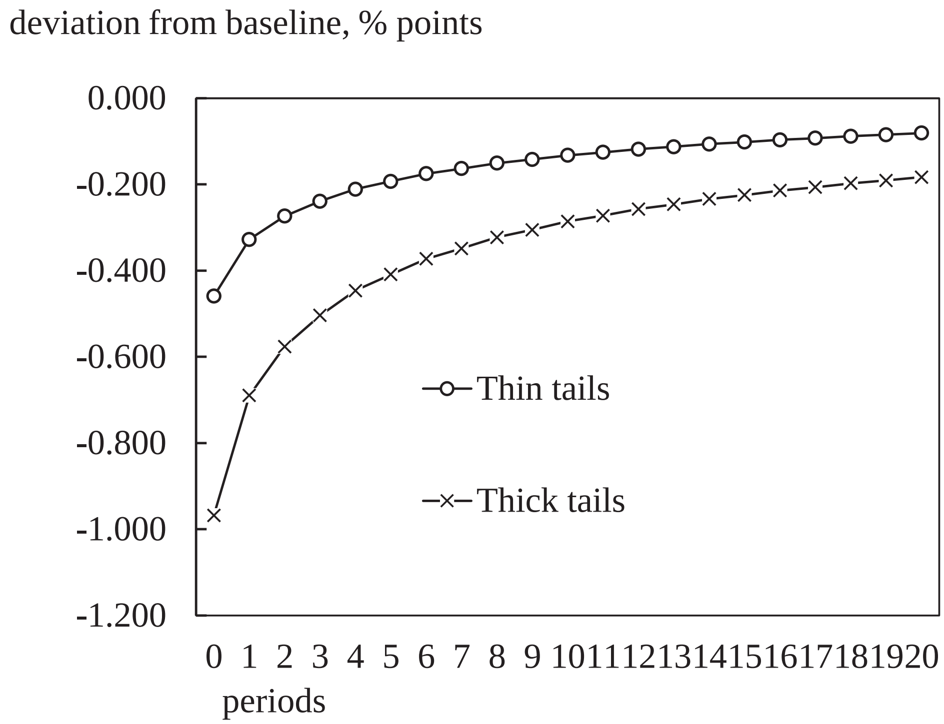


Figure 4: Entry Rate with Different Tail Parameters

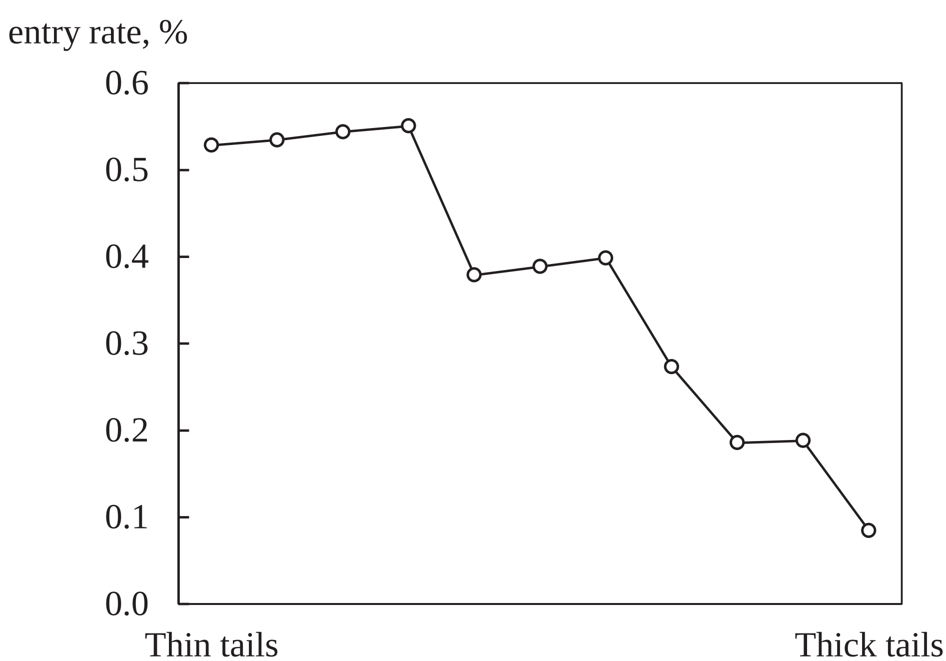


Figure 5: Dynamic Olley-Pakes Decomposition for Japan

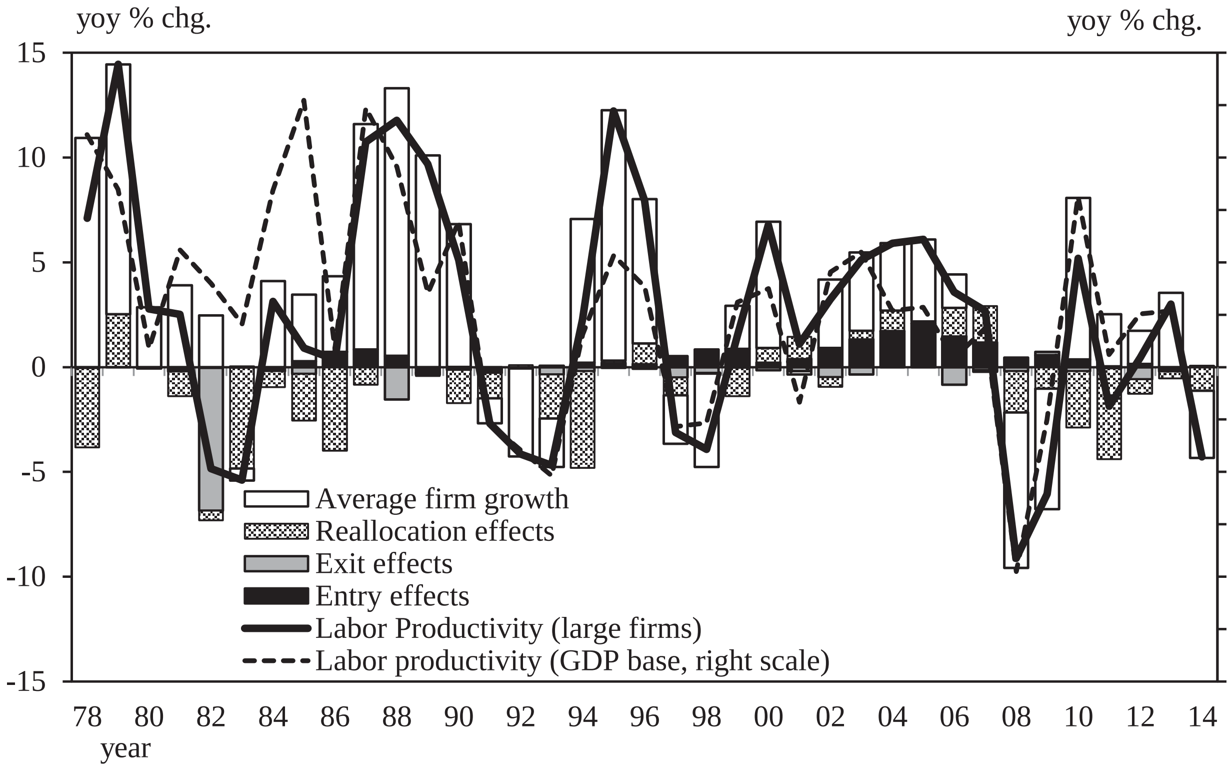


Figure 6: Dynamic Olley-Pakes Decomposition for the U.S.

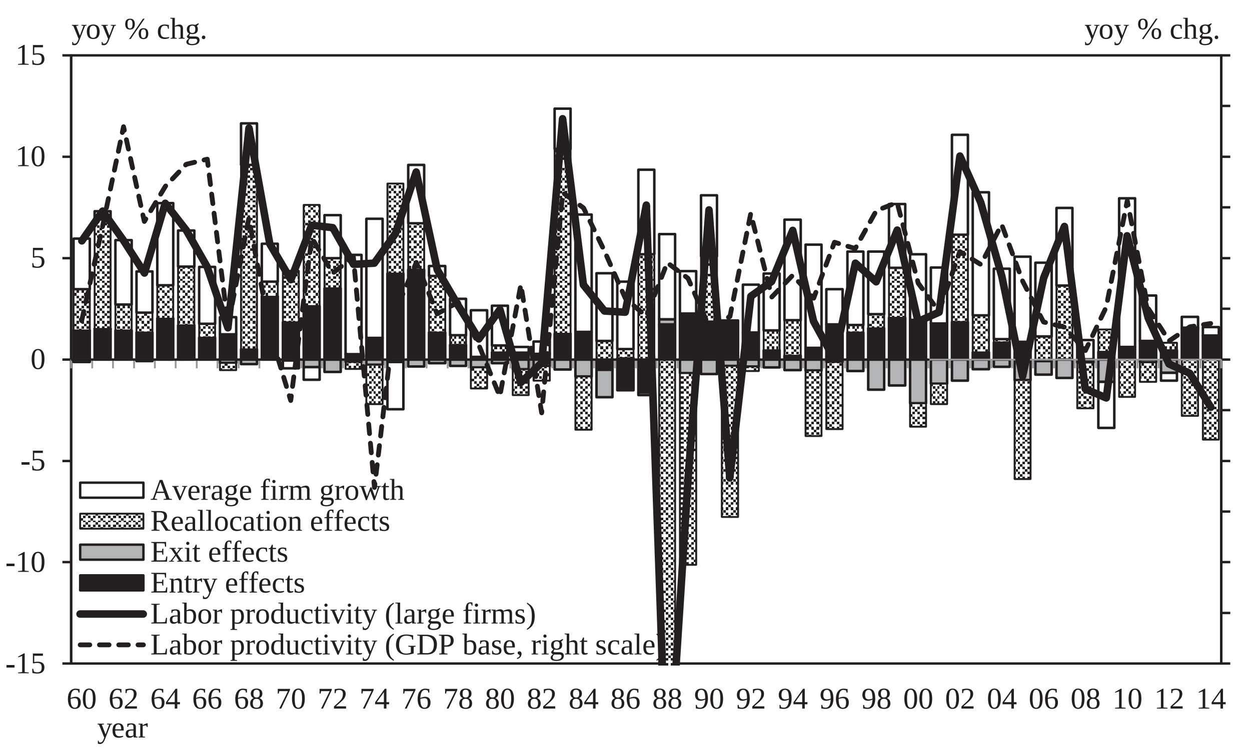


Figure 7(a): Decomposition of Entry Contributions (U.S.)

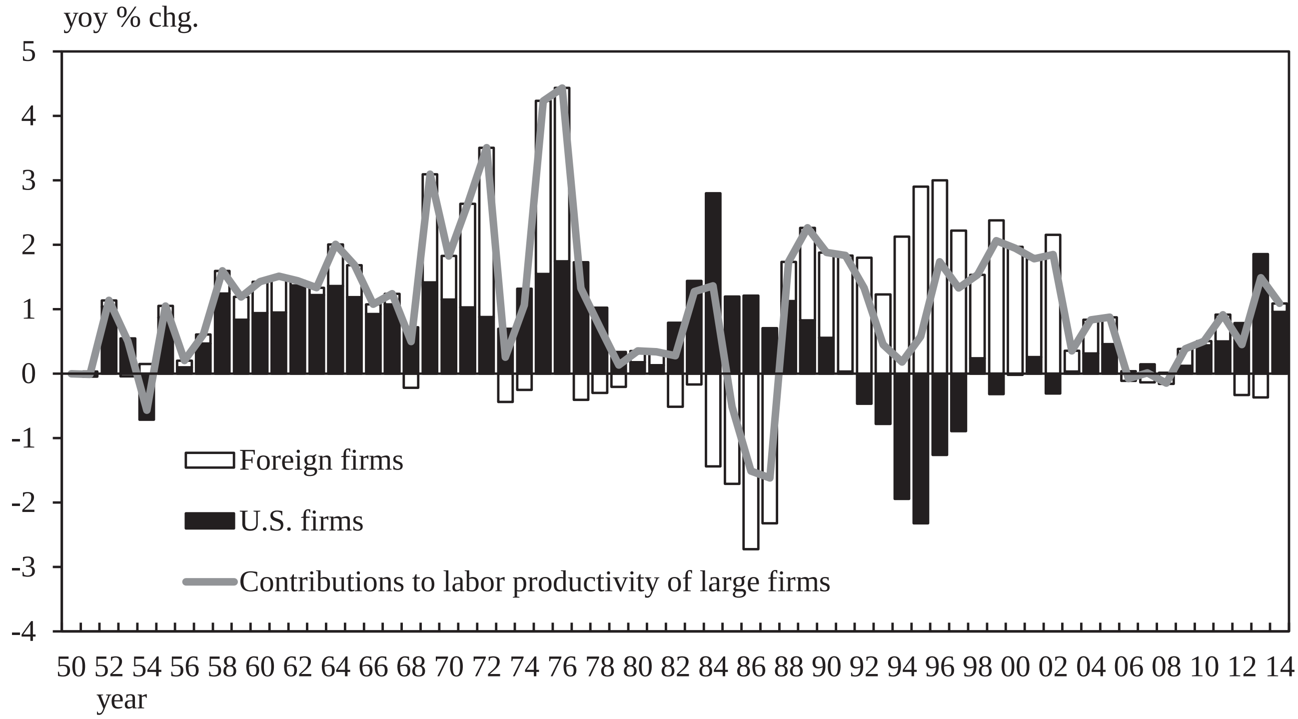


Figure 7(b): Entry Contributions of Foreign Firms (U.S.)

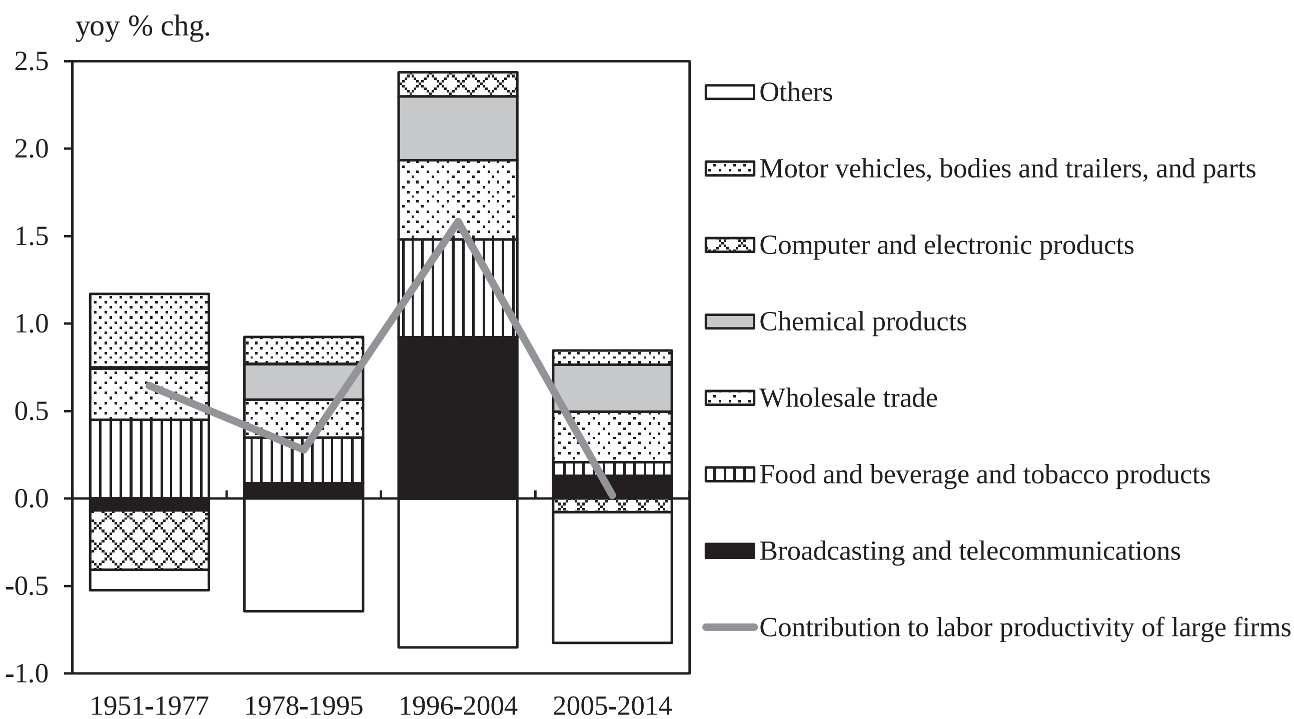
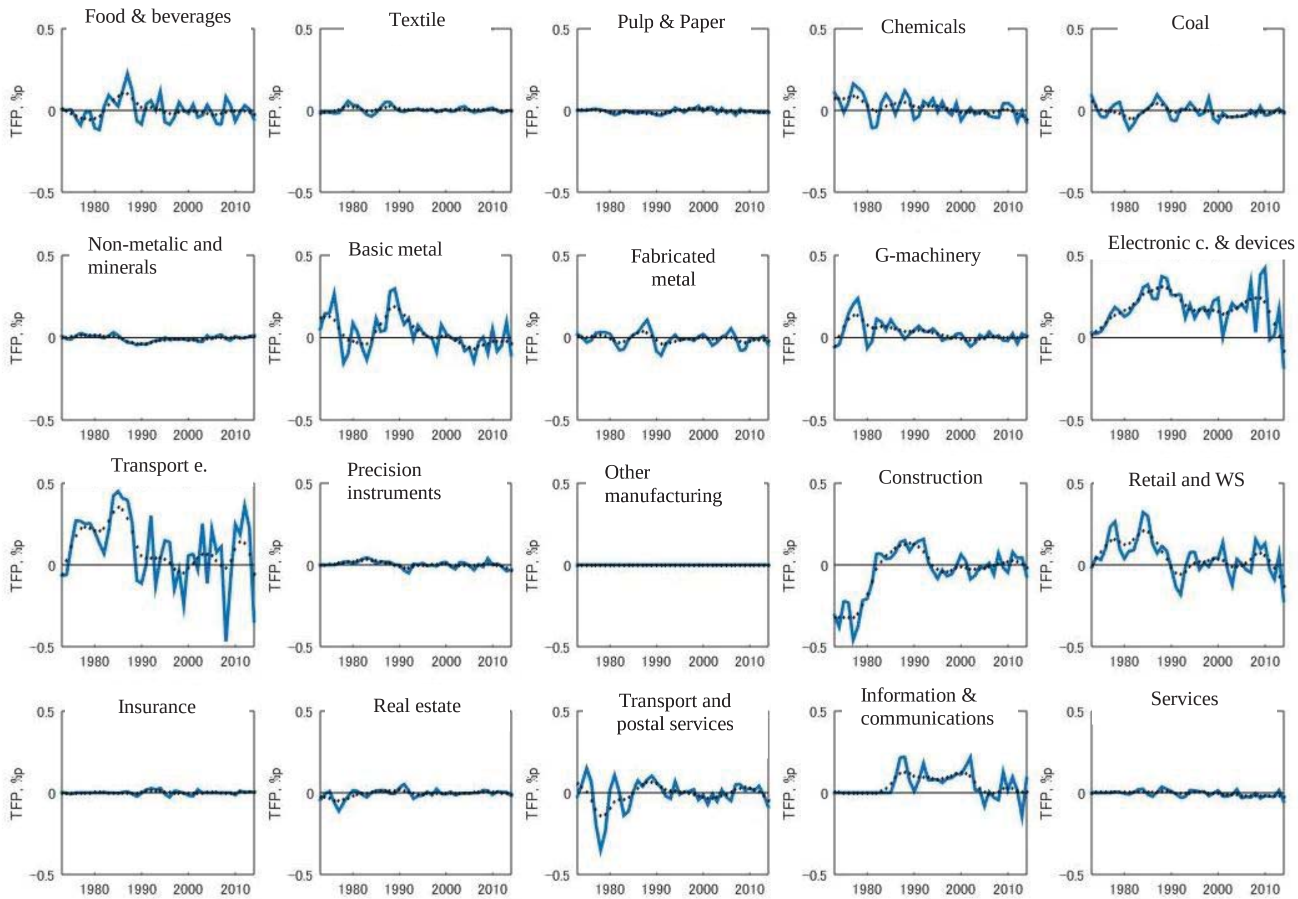


Table 3: Granular Regressions

	Japan						U.S.					
	Labor Productivity			TFP			Labor Productivity			TFP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.485 *	0.286	-0.051	0.775 ***	0.639 ***	0.712 ***	1.326 ***	1.457 ***	1.478 ***	0.663 ***	0.775 ***	0.775 ***
	(0.271)	(0.329)	(0.551)	(0.130)	(0.182)	(0.195)	(0.027)	(0.159)	(0.148)	(0.084)	(0.063)	(0.067)
Granular residua	1.695 ***	1.696 ***	1.880 ***	0.763 **	0.763 **	0.740 **	1.641 ***	1.725 ***	1.817 ***	1.944 ***	2.016 ***	2.021 ***
(GR)	(0.542)	(0.495)	(0.480)	(0.318)	(0.281)	(0.276)	(0.547)	(0.661)	(0.604)	(0.524)	(0.616)	(0.613)
GR(-1)*D	2.947 *	3.050 **	3.307 **	1.324 **	1.394 **	1.319 ***	1.065 **	1.101 **	1.112 ***	1.423 ***	1.453 ***	1.452 ***
	(1.531)	(1.459)	(1.299)	(0.583)	(0.611)	(0.151)	(0.168)	(0.209)	(0.202)	(0.190)	(0.225)	(0.214)
GR(-2)*D	1.188 *	1.177	1.549	0.965 **	0.958 **	0.879 ***	0.728 **	0.680 **	0.679 **	0.954 **	0.914 **	0.914 **
	(0.636)	(0.805)	(0.884)	(0.415)	(0.437)	(0.281)	(0.346)	(0.295)	(0.281)	(0.441)	(0.405)	(0.384)
GR(-1)*(1-D)			1.733 *			-0.112			0.801 ***			0.188
			(0.924)			(0.313)			(0.156)			(0.213)
GR(-2)*(1-D)			-0.430			-0.238			0.384			-0.064
			(0.429)			(0.594)			(0.270)			(0.310)
Net entry	-0.043			-0.048			0.147 *			0.312 ***		
	(0.091)			(0.058)			(0.080)			(0.050)		
Entry		1.824	2.527 *		1.235	1.275		0.098	0.075		0.270 ***	0.269 ***
		(1.293)	(0.916)		(0.826)	(0.915)		(0.113)	(0.087)		(0.065)	(0.061)
Exit		-0.142	-0.190 *		-0.116 ***	-0.113 ***		0.367	0.385		0.499 *	0.495 *
		(0.086)	(0.097)		(0.030)	(0.025)		(0.351)	(0.352)		(0.291)	(0.292)
Reallocation	0.315 *	0.281 **	0.331 **	0.139 **	0.116 *	0.112 **	0.051 *	0.051 **	0.049 **	0.069 ***	0.068 ***	0.068 ***
	(0.128)	(0.135)	(0.126)	(0.064)	(0.065)	(0.048)	(0.026)	(0.024)	(0.022)	(0.019)	(0.017)	(0.015)
Sample period	1979 - 2014	1979 - 2014	1979 - 2014	1979 - 2014	1979 - 2014	1979 - 2014	1952 - 2014	1952 - 2014	1952 - 2014	1952 - 2014	1952 - 2014	1952 - 2014
R2	0.380	0.411	0.460	0.383	0.444	0.450	0.312	0.319	0.330	0.385	0.389	0.389
Adjusted R2	0.276	0.289	0.300	0.280	0.329	0.288	0.252	0.246	0.230	0.331	0.323	0.299
SE of regression	1.695	1.680	1.667	0.826	0.797	0.822	1.209	1.214	1.226	1.342	1.350	1.374

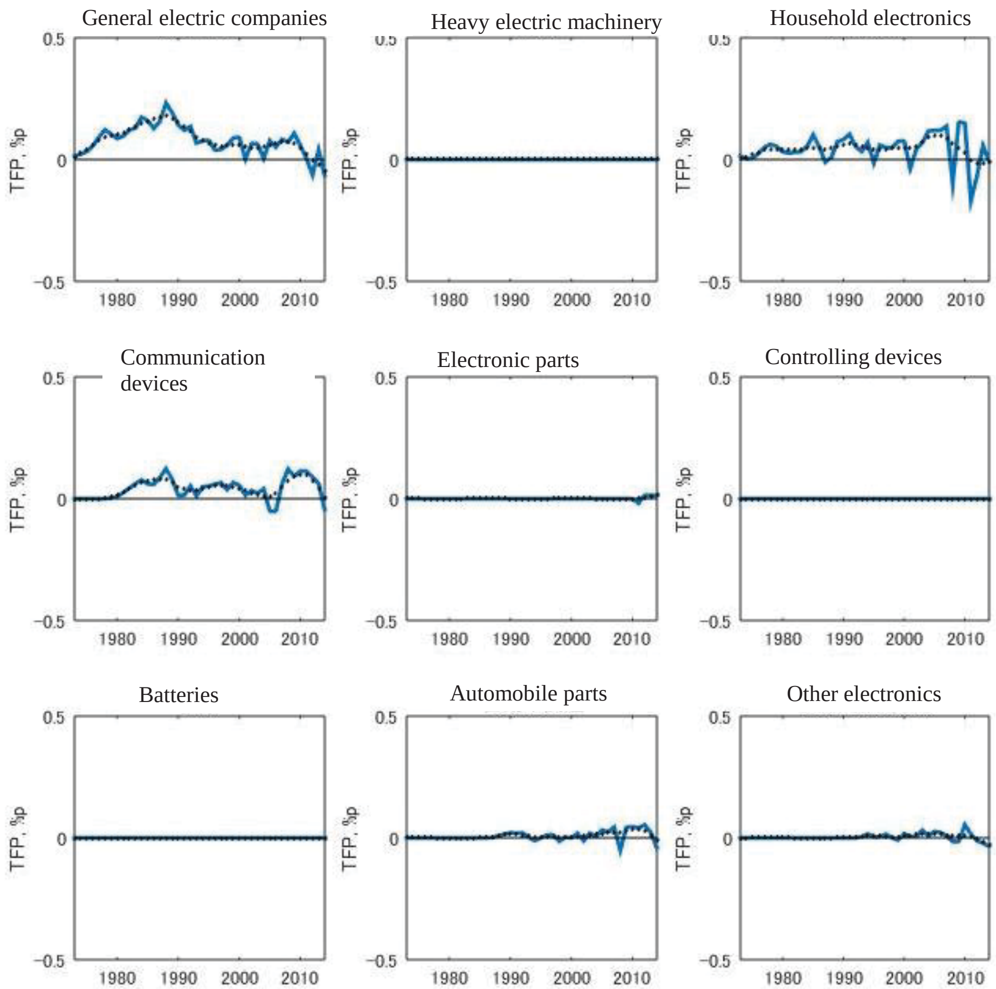
Note: Estimation is done by OLS. ***, **, * indicate significant levels of 1%, 5%, 10% respectively. Numbers in parenthesis are Heteroskedasticity and Autocorelattion Consistent standard errors.
D is a dummy variable 1979 - 1993 for Japan and 1952 - 1989 for the U.S.

Figure 8: Sectoral Contributions From the Granular Regression (Japan<1>)



Note: Dotted lines indicate HP filtered trends.

Figure 9: Sectoral Contributions From the Granular Regression (Japan<2>)

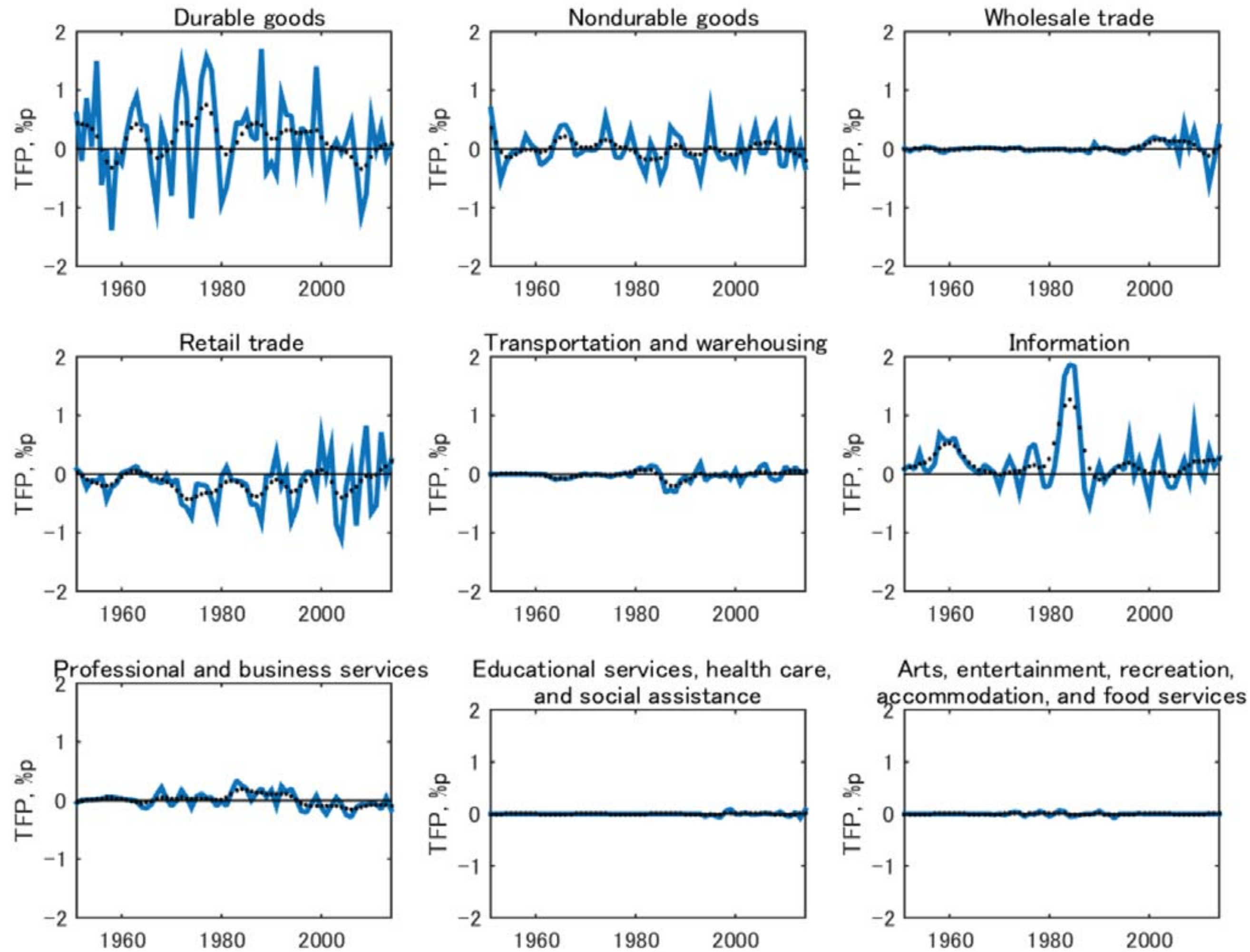


Note: Dotted lines indicate HP filtered trends.

Table 4: Contributions to TFP Growth by Firms (Japan)

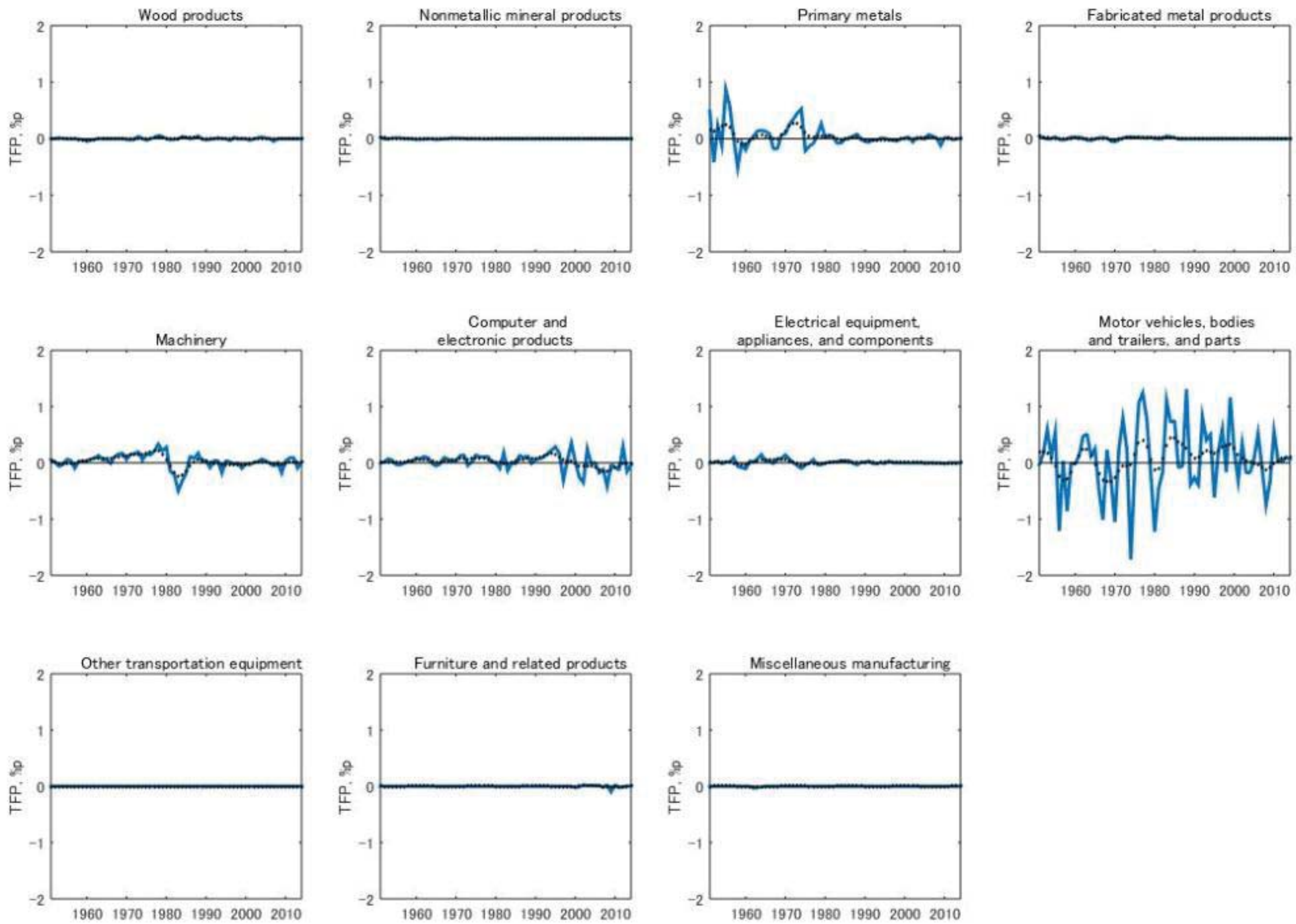
	Lowest 1	2	3	4	5	5	4	3	2	Highest 1
1980	SHIMIZU CORP	JFE SHOJI TRADE	BRIDGESTONE	OOBAYASHI CORP	MITSUBISHI HEAVY CO.	MARUHA NICHIRO	TOYOTA TSUSHO	N. STEEL & S. METAL	MAZDA	NISSAN
1981	BRIDGESTONE	TOYOTA	TOYOTA CAR SALES	ISUZU	SEKISUI HOUSE	HONDA	NIPPON YUSEN	TOYOTA TSUSHO	MAZDA	NISSAN
1982	BRIDGESTONE	N. STEEL & S. METAL	TOYOTA CAR SALES	NISSAN	MITSUBISHI CHEMICAL	MATSUSHITA ELEC. TRA	MAZDA	HITACHI	CARGILL JAPAN	MITSUBISHI HEAVY CO.
1983	N. STEEL & S. METAL	JFE ENGINEERING	JAPAN ENERGY	SUMITOMO METAL	FURUKAWA ELECTRIC	HITACHI	KIRIN HOLDINGS	CARGILL JAPAN	SHIMIZU CORP	TOYOTA
1984	JFE ENGINEERING	SUMITOMO METAL	JAPAN ENERGY	IHI	MITSUI O.S.K. LINES	PANASONIC	HITACHI	NISSAN	MITSUBISHI HEAVY CO.	TOYOTA
1985	JAPAN ENERGY	IHI	JFE ENGINEERING	MITSUI O.S.K. LINES	ITOMAN	MITSUBISHI MOTORS	HONDA	PANASONIC	MITSUBISHI HEAVY CO.	NISSAN
1986	TOYOTA	JAPAN ENERGY	MITSUBISHI CHEMICAL	SEIYU GK	DIC	JAPAN TOBACCO	MAZDA	MITSUBISHI MOTORS	HONDA	NISSAN
1987	JAPAN ENERGY	HITACHI HOME APP.	MITSUBISHI CHEMICAL	MITSUBISHI HEAVY CO.	ARABIAN OIL	MITSUBISHI MOTORS	KIRIN HOLDINGS	BRIDGESTONE	JAPAN TOBACCO	TOYOTA
1988	NIPPON YUSEN	SEIYU GK	MITSUBISHI HEAVY CO.	MITSUBISHI CHEMICAL	AC REAL ESTATE	NIPPON EXPRESS	KOBE STEEL	TOSHIBA	HITACHI	TOYOTA
1989	MITSUBISHI MOTORS	MAZDA	ASAHI GLASS	HONDA	KUMAGAYA CORP	JFE STEEL	HITACHI	SUMITOMO METAL	N. STEEL & S. METAL	TOYOTA
1990	MITSUBISHI MOTORS	NISSAN	JAPAN TOBACCO	HONDA	FUJITSU	JFE STEEL	SHIMIZU CORP	NEC	HITACHI	N. STEEL & S. METAL
1991	JFE ENGINEERING	JFE SHOJI TRADE	ASAHI GLASS	TOYOTA	FUJITSU	NEC	HITACHI	KASHIMA CORP	SHIMIZU CORP	N. STEEL & S. METAL
1992	JFE SHOJI TRADE	JFE ENGINEERING	CARGILL JAPAN	HANWA	JAPAN AIRLINES	MITSUBISHI MOTORS	KASHIMA CORP	HITACHI	SHIMIZU CORP	N. STEEL & S. METAL
1993	TOYOTA	MAZDA	SUMITOMO METAL	TOYOTA TSUSHO	MITSUBISHI MOTORS	PANASONIC	NEC	TOSHIBA	N. STEEL & S. METAL	HITACHI
1994	TOYOTA	TAISEI CORP	SHIMIZU CORP	OOBAYASHI CORP	TOYOTA TSUSHO	MITSUBISHI HEAVY CO.	JAPAN TOBACCO	BRIDGESTONE	N. STEEL & S. METAL	NISSAN
1995	JAPAN TOBACCO	KASHIMA CORP	SHIMIZU CORP	MAZDA	KIRIN HOLDINGS	TOSHIBA	HITACHI	THE DAIEI	NISSAN	TOYOTA
1996	JAPAN TOBACCO	MITSUBISHI MOTORS	SHIMIZU CORP	KIRIN HOLDINGS	TOYOTA TSUSHO	HONDA	FUJITSU	PANASONIC	NISSAN	TOYOTA
1997	TOYOTA	JAPAN TOBACCO	KASHIMA CORP	TAISEI CORP	NISSAN	MAZDA	NEC	HONDA	PANASONIC	FUJITSU
1998	TOYOTA	MITSUBISHI CHEMICAL	TOYOTA TSUSHO	KOBE STEEL	KASHIMA CORP	HITACHI	JAPAN TOBACCO	FUJITSU	BRIDGESTONE	NISSAN
1999	TOYOTA	NISSAN	BRIDGESTONE	MAZDA	TOYOTA TSUSHO	TOSHIBA	NEC	HITACHI	FUJITSU	JAPAN TOBACCO
2000	BRIDGESTONE	THE DAIEI	KIRIN HOLDINGS	KDDI	SEKISUI HOUSE	PANASONIC	TOSHIBA	HITACHI	NEC	NISSAN
2001	TOYOTA	PANASONIC	MITSUBISHI ELECTRIC	MITSUBISHI CHEMICAL	MITSUBISHI HEAVY CO.	SUMITOMO METAL	KDDI	FUJITSU	AEON	NISSAN
2002	TOYOTA	ITO-YOKADO	BRIDGESTONE	MITSUBISHI HEAVY CO.	KASHIMA CORP	MAZDA	TOSHIBA	MITSUBISHI MOTORS	NISSAN	NTT DOCOMO
2003	MITSUBISHI MOTORS	ITO-YOKADO	BRIDGESTONE	AEON	MITSUBISHI HEAVY CO.	MAZDA	TOSHIBA	FUJITSU	NISSAN	TOYOTA
2004	NISSAN	BRIDGESTONE	MAZDA	NTT DOCOMO	JFE HOLDINGS	SONY	FUJITSU	AEON	PANASONIC	JAPAN TOBACCO
2005	BRIDGESTONE	KDDI	AEON	JFE HOLDINGS	NEC	SONY	ITO-YOKADO	PANASONIC	TOYOTA	NISSAN
2006	NEC	JAPAN TOBACCO	AEON	JFE HOLDINGS	N. STEEL & S. METAL	JX NIPPON MINING	SONY	PANASONIC	SEVEN &I HOLDINGS	TOYOTA
2007	JAPAN TOBACCO	AEON	MITSUBISHI CHEM. HD	SUMITOMO ELECTRIC	TOYOTA TSUSHO	JX NIPPON MINING	DENSO	SONY	PANASONIC	NISSAN
2008	TOYOTA	NISSAN	TOYOTA TSUSHO	DENSO	N. STEEL & S. METAL	MITSUBISHI HEAVY CO.	FUJITSU	NEC	SEVEN &I HOLDINGS	JAPAN TOBACCO
2009	TOYOTA TSUSHO	JX NIPPON MINING	N. STEEL & S. METAL	HONDA	CANON	NTT DOCOMO	PANASONIC	AEON	SEVEN &I HOLDINGS	FUJITSU
2010	JAPAN TOBACCO	BRIDGESTONE	HITACHI	KASHIMA CORP	SHIMIZU CORP	DENSO	TOSHIBA	NEC	PANASONIC	NISSAN
2011	PANASONIC	TOSHIBA	SONY	SHARP	SEVEN &I HOLDINGS	DENSO	NEC	TOYOTA	FUJITSU	NISSAN
2012	TOYOTA TSUSHO	PANASONIC	TOSHIBA	SONY	N. STEEL & S. METAL	SHARP	NEC	DENSO	TOYOTA	NISSAN
2013	AEON	KDDI	SOFT BANK GROUP	NTT DOCOMO	NEC	TOSHIBA	SEVEN &I HOLDINGS	FUJITSU	TOYOTA TSUSHO	TOYOTA
2014	TOYOTA	AEON	NISSAN	SHARP	N. STEEL & S. METAL	SUBARU	SONY	MITSUBISHI HEAVY CO.	NTT DOCOMO	SOFT BANK GROUP

Figure 10: Sectoral Contributions From the Granular Regression (U.S.<1>)



Note: Dotted lines indicate HP filtered trends.

Figure 11: Sectoral Contributions From the Granular Regression (U.S.<2>)



Note: Dotted lines indicate HP filtered trends.

Table 5: Contributions to TFP growth by Firms (U.S.)

Year	Lowest 1	2	3	4	5	5	4	3	2	Highest 1
1955	G.E.	ESMARK	SAFEWAY	CBS	BOEING	FORD	BETHLEHEM STEEL	AT&T	US STEEL	G.M.
1956	FORD	G.M.	G.E.	CHRYSLER	ESMARK	NAVISTAR	ANACONDA	BETHLEHEM STEEL	AT&T	US STEEL
1957	G.M.	SEARS	G.E.	FORD	SAFEWAY	ROCKWELL AUTOMATION'	UNITED TECHNOLOGIES	GENERAL DYNAMICS	AT&T	CHRYSLER
1958	G.M.	FORD	US STEEL	SEARS	BETHLEHEM STEEL	BOEING	CBS	G.E.	ESMARK	AT&T
1959	JC PENNY	ROCKWELL AUTO	NAVISTAR	REPUBLIC STEEL	SAFEWAY	ESMARK	PACIFIC BELL	G.E.	LOCKHEED MARTIN	AT&T
1960	FORD	ROCKWELL AUTO	US STEEL	UNITED TECHNOLOGIES	G.E.	CHRYSLER	FOOT LOCKER	PACIFIC BELL	G.M.	AT&T
1961	DU PONT	SEARS	GREAT ATLANTIC & PAC TE	GENERAL FOODS	CHRYSLER	BICOASTAL	PACIFIC BELL	JC PENNY	FORD	AT&T
1962	BOEING	GENERAL FOODS	SAFEWAY	BEAM	PHARMACIA	GENERAL DYNAMICS	JC PENNY	FORD	AT&T	G.M.
1963	GENERAL DYNAMICS	RALSTON PURINA-CONSOLIDATEI	RALSTON PURINA	BOEING	ANDERSON CLAYTON	US STEEL	JC PENNY	FORD	AT&T	G.M.
1964	IBM	SANTA FE PACIFIC	GREAT ATLANTIC & PAC TE	LOCKHEED MARTIN	SAFEWAY	DU PONT	JC PENNY	G.M.	AT&T	ROCKWELL AUTO
1965	IBM	SANTA FE PACIFIC	GREAT ATLANTIC & PAC TE	TENNECO	GENERAL DYNAMICS	KROGER	GOODYEAR	FORD	G.M.	G.E.
1966	G.M.	JC PENNY	BOEING	SANTA FE PACIFIC	UNION CARBIDE	GOODYEAR	ANACONDA	ITT	ESMARK	G.E.
1967	FORD	CHRYSLER	G.M.	JC PENNY	US STEEL	GRACE (W R)	UNITED TECHNOLOGIES	ITT	AT&T	G.E.
1968	LTV	GENERAL FOODS	HILLSHIRE BRANDS	SAFEWAY	LOCKHEED MARTIN	UNITED TECHNOLOGIES	MCDONNELL DOUGLAS	GENERAL DYNAMICS	ITT	IBM
1969	CHRYSLER	G.E.	LOCKHEED MARTIN	AVCO	SAFEWAY	LTV	ESMARK	FOOT LOCKER	SEARS HOLDINGS	ITT
1970	G.M.	G.E.	JC PENNY	CHRYSLER	AT&T	FIRESTONE	ESMARK	ROCKWELL AUTO	BOEING	LTV
1971	MCDONNELL DOUGLAS	JC PENNY	G.E.	BEAM	RALSTON PURINA-C	G.M.	ITT	LOCKHEED MARTIN	BOEING	LTV
1972	SEARS	MCCRORY	JC PENNY	KROGER	RALSTON PURINA-C	IBM	AT&T	CHRYSLER	G.M.	FORD
1973	SEARS	JC PENNY	SAFEWAY	GENERAL DYNAMICS	COLGATE-PALMOLIVE	ITT	FORD	LTV	US STEEL	G.M.
1974	G.M.	FORD	CHRYSLER	SEARS	CBS	ARMCO	UNION CARBIDE	BETHLEHEM STEEL	DOW CHEMICAL	US STEEL
1975	FORD	UNITED TECHNOLOGIES	SEARS	G.M.	G.E.	INTL STANDARD ELECTRIC	AT&T	GRACE (W R)	TENNECO	FOOT LOCKER
1976	ESMARK	SEARS	RALSTON PURINA-C	RALSTON PURINA	FOOT LOCKER	TENNECO	FORD	CHRYSLER	AT&T	G.M.
1977	ESMARK	SEARS HOLDINGS	SAFEWAY	RALSTON PURINA-C	RALSTON PURINA	CHRYSLER	ITT	AT&T	FORD	G.M.
1978	KROGER	JONES & LAUGHLIN INDS	SEARS	LTV	PEPSICO	AT&T	ITT	FORD	G.M.	CHRYSLER
1979	G.M.	SEARS HOLDINGS	KROGER	AT&T	FORD	DU PONT	ASHLAND	DOW CHEMICAL	CHRYSLER	ITT
1980	G.M.	FORD	AT&T	SEARS HOLDINGS	KRAFT GENERAL FOODS	ITT	TENNECO	UNITED TECHNOLOGIE	ASHLAND	SEARS
1981	G.M.	FORD	ITT	KRAFT GENERAL FOODS	SAFEWAY	TENNECO	FOOT LOCKER	DU PONT	UNITED TECHNOLOGIES	SEARS
1982	FORD	KROGER	ITT	G.M.	IBP	PACIFIC BELL	SEARS	IBM	DU PONT	AT&T
1983	ITT	CATERPILLAR	TRANSWORLD L. TRUST	FLAGSTAR	ASHLAND	FORD	IBM	DU PONT	G.M.	AT&T
1984	ITT	NABISCO GROUP HOLDINGS	ASHLAND	TENNECO	AMERICAN STORES	CHRYSLER	IBM	G.M.	FORD	AT&T
1985	DU PONT	SEARS HOLDINGS	TENNECO	HONEYWELL INTERNATION/	NABISCO GROUP HOLDINGS	G.E.	IBM	G.M.	FORD	AT&T
1986	DU PONT	G.M.	ASHLAND	BURLINGTON N. SANTA FE	TENNECO	UNION CARBIDE	DIRECTV	COCA-COLA	AT&T	FORD
1987	G.M.	AT&T	BOEING	DU PONT	CHRYSLER	UNION CARBIDE	KRAFT GENERAL FOODS	COCA-COLA	G.E.	FORD
1988	AT&T	SEARS	ALTRIA GROUP	BOEING	JC PENNY	ITT	CHRYSLER	G.E.	G.M.	FORD
1989	G.M.	FORD	KROGER	MCDONNELL DOUGLAS	DOW CHEMICAL	G.E.	KRAFT GENERAL FOODS	SEARS	NABISCO GROUP HOLDING	ALTRIA GROUP
1990	CHRYSLER	G.M.	FORD	GEORGIA-PACIFIC	GEORGIA-PACIFIC CP - C	DU PONT	SEARS	BOEING	AT&T	IBM
1991	G.M.	AT&T	FORD	CHRYSLER	DOW CHEMICAL	ALTRIA GROUP	SUPERVALU	MCDONNELL DOUGLAS	SEARS HOLDINGS	WAL-MART STORES
1992	KROGER	CBS	PROCTER & GAMBLE	SUPERVALU	NABISCO GROUP HOLDINGS	G.M.	CHRYSLER	IBM	G.E.	FORD
1993	ALTRIA GROUP	DU PONT	WAL-MART STORES	'TIME WARNER INC-OLD'	NABISCO GROUP HOLDINGS	G.E.	FORD	CHRYSLER	IBM	G.M.
1994	SEARS HOLDINGS	ITT	BOEING	G.E.	WAL-MART STORES	AT&T	FORD	IBM	CHRYSLER	G.M.
1995	SEARS	G.M.	LOCKHEED MARTIN	CHRYSLER	MCKESSON	SEARS HOLDINGS	HP	DOW CHEMICAL	ALTRIA GROUP	G.E.
1996	LUCENT TECHNOLOGIES	FORD	BOEING	JC PENNY	IBM	DU PONT	COCA-COLA	CHRYSLER	G.M.	AT&T
1997	IBM	G.E.	WAL-MART STORES	COMPAQ COMPUTER	COCA-COLA	BOEING	FORD	JC PENNY	PEPSICO	G.M.
1998	G.M.	DU PONT	COMPAQ COMPUTER	FORD	IBM	G.E.	ALTRIA GROUP	WAL-MART STORES	BOEING	AT&T
1999	WAL-MART STORES	AT&T	G.E.	COCA-COLA	AMERICAN AIRLINES GROUP	MCKESSON	COMPAQ COMPUTER	BOEING	HP	G.M.
2000	ALTRIA GROUP	BOEING	MCI	WORLDCOM-C	AT&T	BERGEN BRUNSWIG	WAL-MART STORES	TARGET	FORD	G.E.
2001	FORD	WORLDCOM-C	COMPAQ COMPUTER	INTEL	IBM	AT&T	MONDELEZ INTERNATIONA	CARDINAL HEALTH	BOEING	ALTRIA GROUP
2002	ALTRIA GROUP	HP	BERKSHIRE HATHAWA	IBM	'LOWE"S COMPANIES INC'	MCI	MCKESSON	AT&T	G.M.	WAL-MART STORES
2003	WAL-MART STORES	'MERCK & CO'	JC PENNY	UNITED TECHNOLOGIES	SAFEWAY	VERIZON COMMUNICATIONS	DOW CHEMICAL	MCKESSON	BERKSHIRE HATHAWA	HP
2004	WAL-MART STORES	SEARS	CVS HEALTH	G.M.	FORD	MOTOROLA SOLUTIONS	DU PONT	G.E.	PFIZER	DOW CHEMICAL
2005	G.M.	G.E.	ALTRIA GROUP	IBM	AT&T	HP	AT&T MOBILITY	CVS HEALTH	DOW CHEMICAL	FORD
2006	MCKESSON	FORD	DELL	IBM	AT&T	G.E.	MOTOROLA SOLUTIONS	SPRINT	ALTRIA GROUP	G.M.
2007	G.M.	WAL-MART STORES	HOME DEPOT	MOTOROLA SOLUTIONS	MEDCO HEALTH SOLUTIONS	CVS HEALTH	AMERISOURCEBERGEN	AT&T	CARDINAL HEALTH	FORD
2008	G.M.	BERKSHIRE HATHAWA	HP	FORD	BOEING	MONDELEZ INTERNATIONAL	G.E.	ALTRIA GROUP	ARCHER-DANIELS-MIDLAN	WAL-MART STORES
2009	G.M.	FORD	DELL	DOW CHEMICAL	CATERPILLAR	CARDINAL HEALTH	VERIZON COMMUNICATION	CVS HEALTH	WAL-MART STORES	BERKSHIRE HATHAWA
2010	MCKESSON	ARCHER-DANIELS-MIDLAND	WAL-MART STORES	BOEING	IBM	DOW CHEMICAL	PFIZER	CARDINAL HEALTH	G.M.	FORD
2011	G.E.	WAL-MART STORES	HP	AMAZON.COM	DELL	CHS	CHRYSLER GROUP	COCA-COLA	ARCHER-DANIELS-MIDLAN	APPLE
2012	MCKESSON	AMERISOURCEBERGEN	MONDELEZ INTERNATIONA	AMAZON.COM	ALPHABET	BOEING	VERIZON COMMUNICATION	CVS HEALTH	APPLE	WAL-MART STORES
2013	MCKESSON	CARDINAL HEALTH	CATERPILLAR	KROGER	ABBOTT LABORATORIES	VERIZON COMMUNICATIONS	EXPRESS SCRIPTS HOLDINC	BERKSHIRE HATHAWA	ALPHABET	AMERISOURCEBERGEN
2014	ARCHER-DANIELS-MIDLAN	APPLE	CARDINAL HEALTH	MICROSOFT	FORD	CHRYSLER GROUP	SPRINT	HCA HOLDINGS	AMERISOURCEBERGEN	MCKESSON

Figure 12: Identification of Demand and Supply Shocks (Japan, 2008)

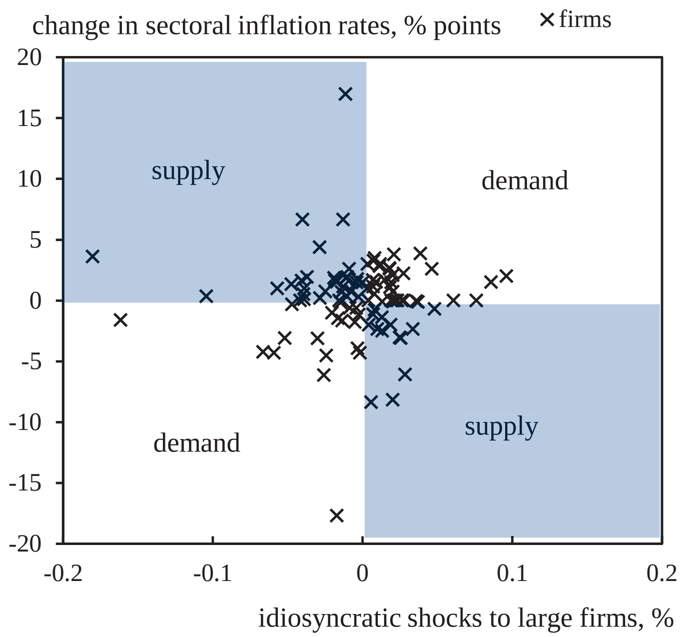


Figure 13: Share of Firms Classified as Demand Shocks

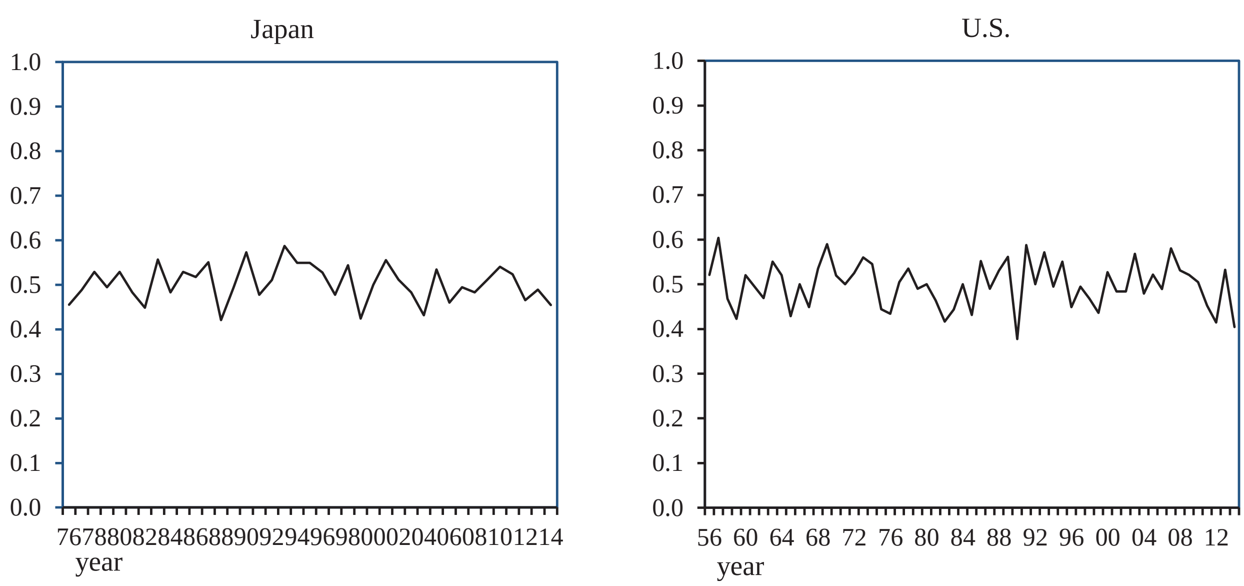
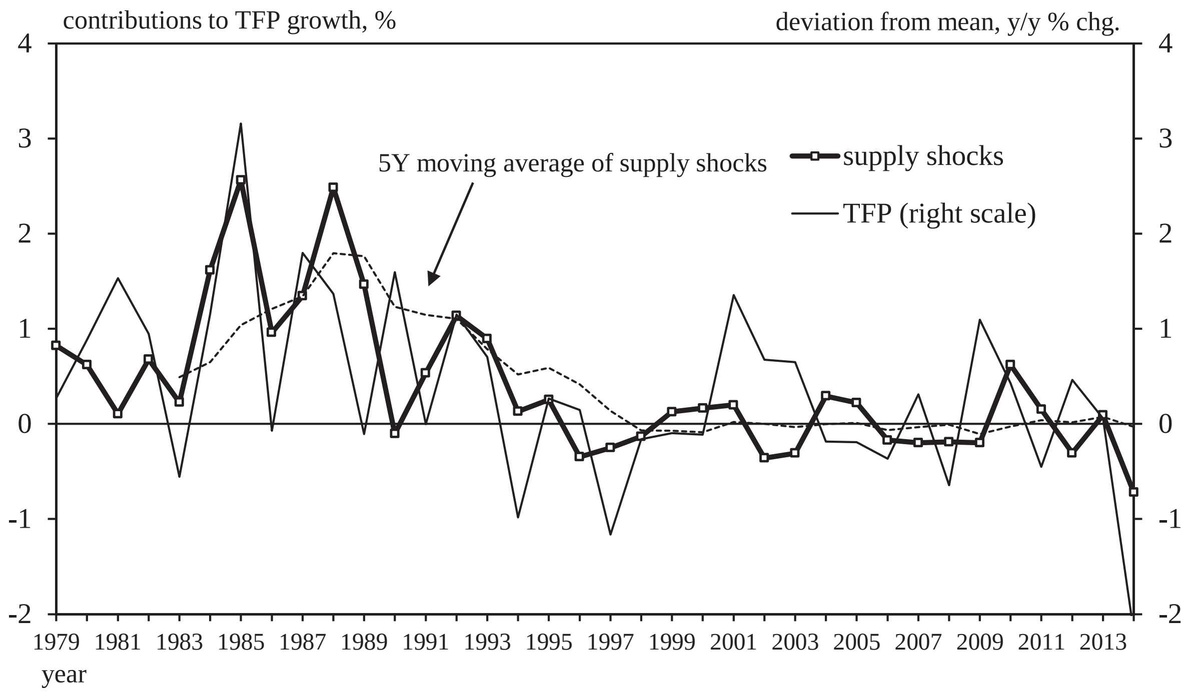


Figure 14: Contributions of Shocks to TFP Growth (Japan)



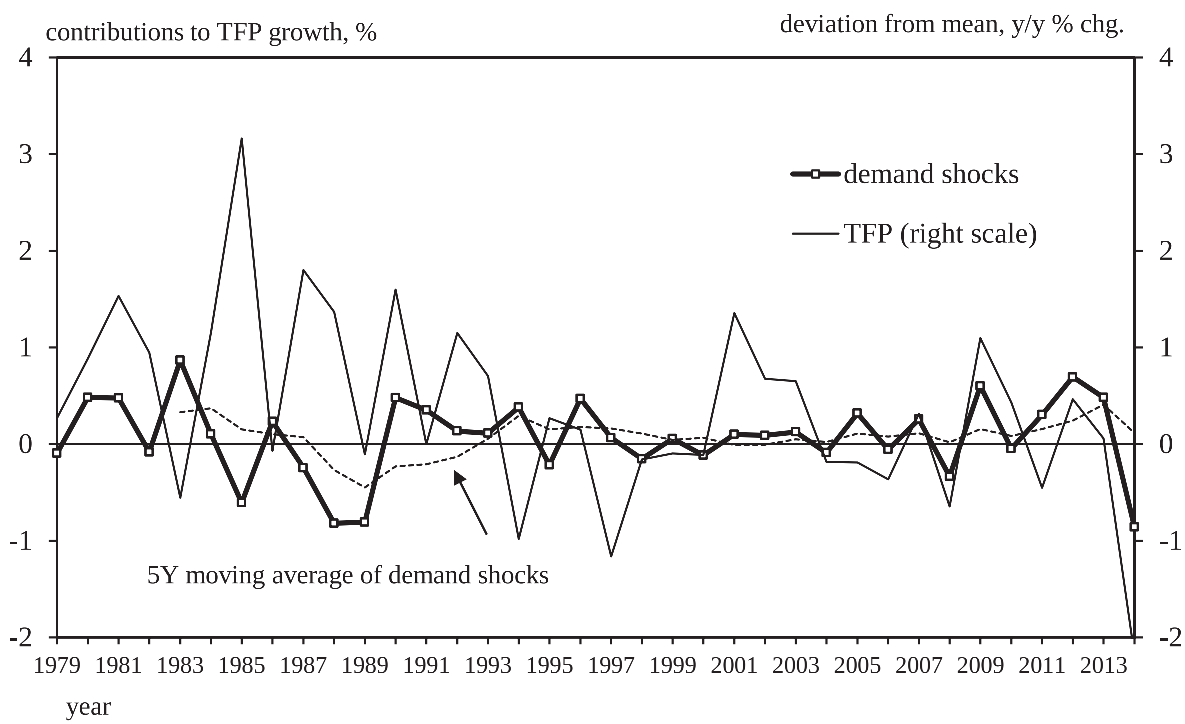
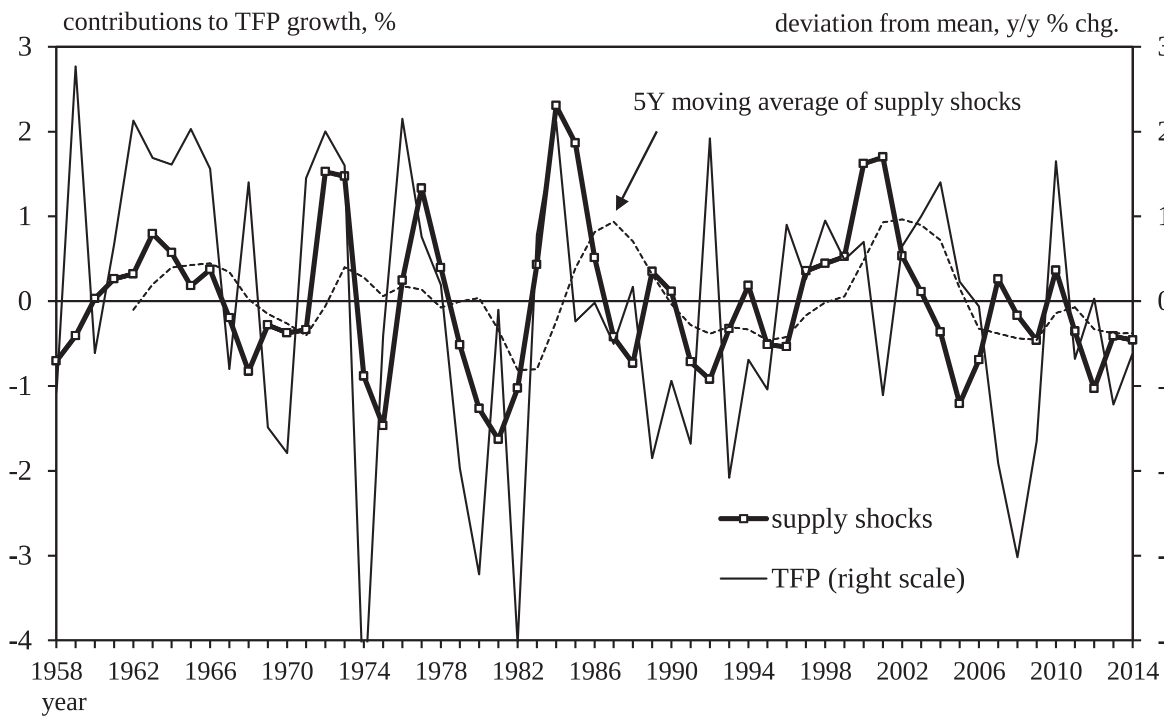


Figure 15: Contributions of Shocks to TFP Growth (U.S.)



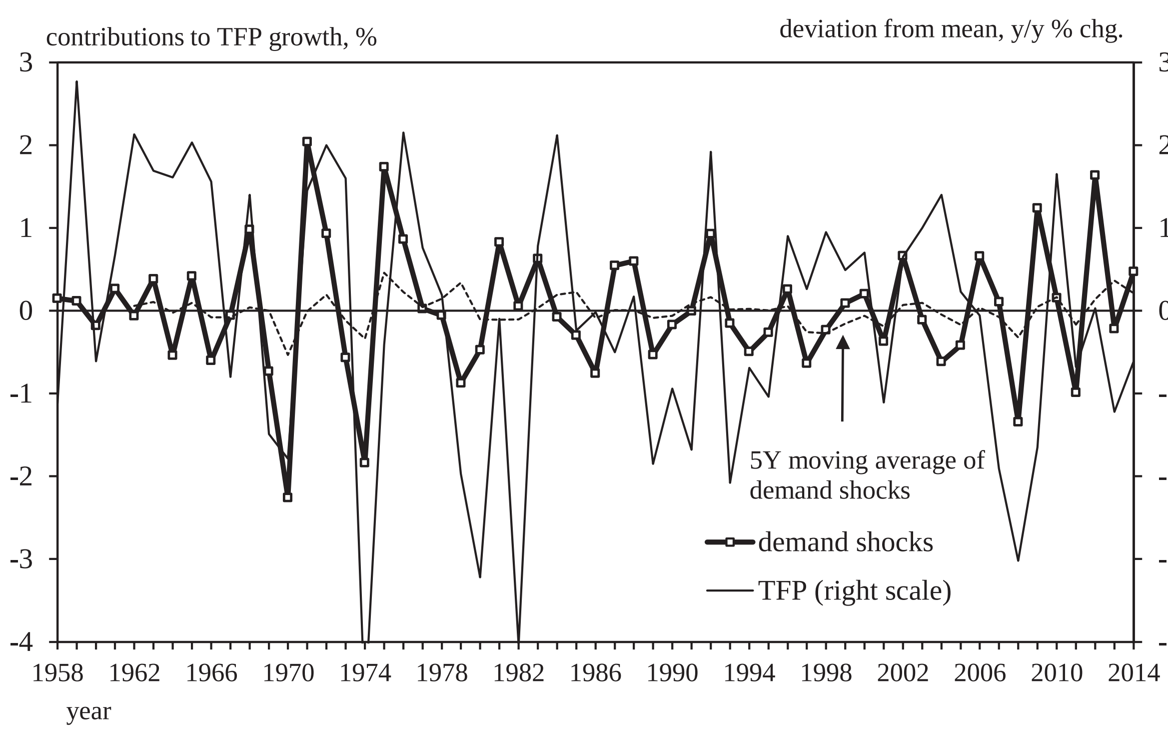
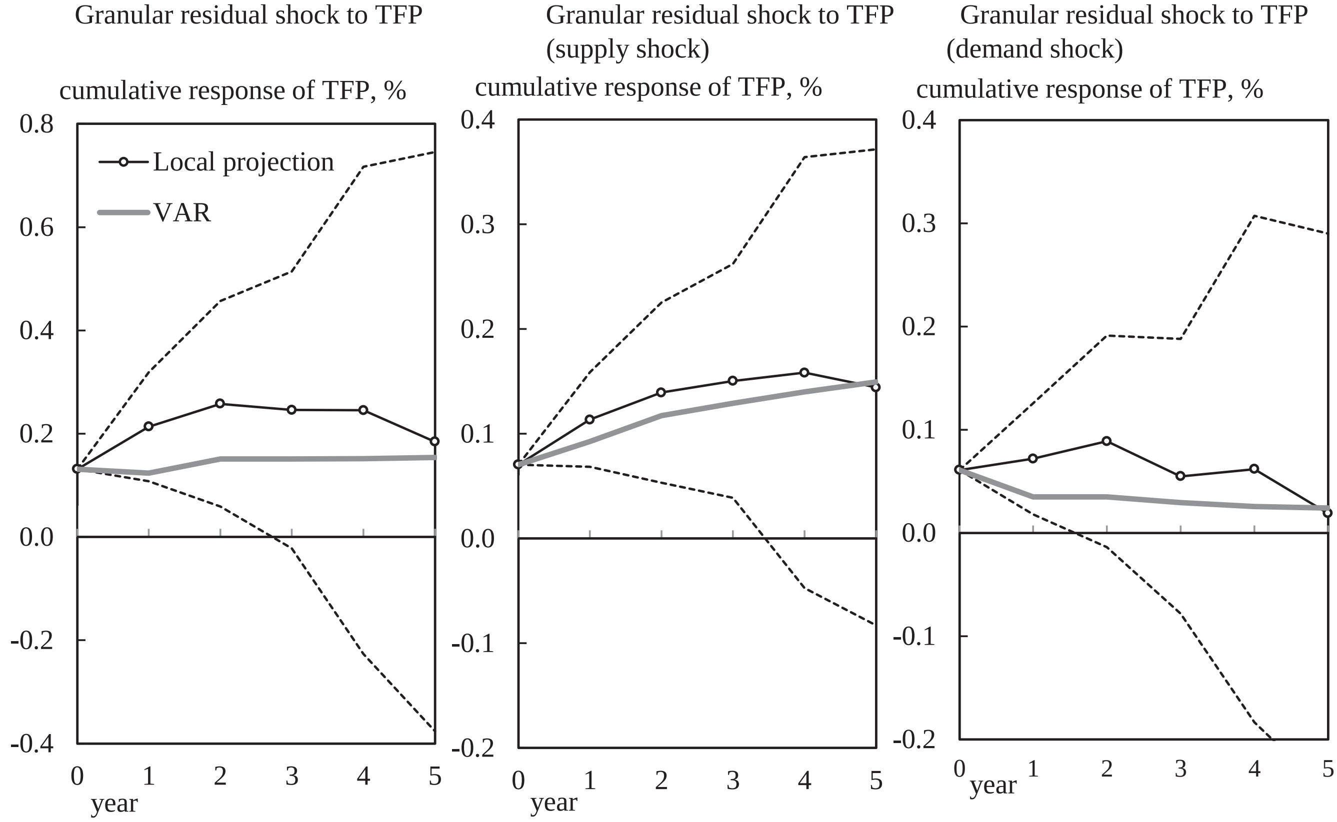
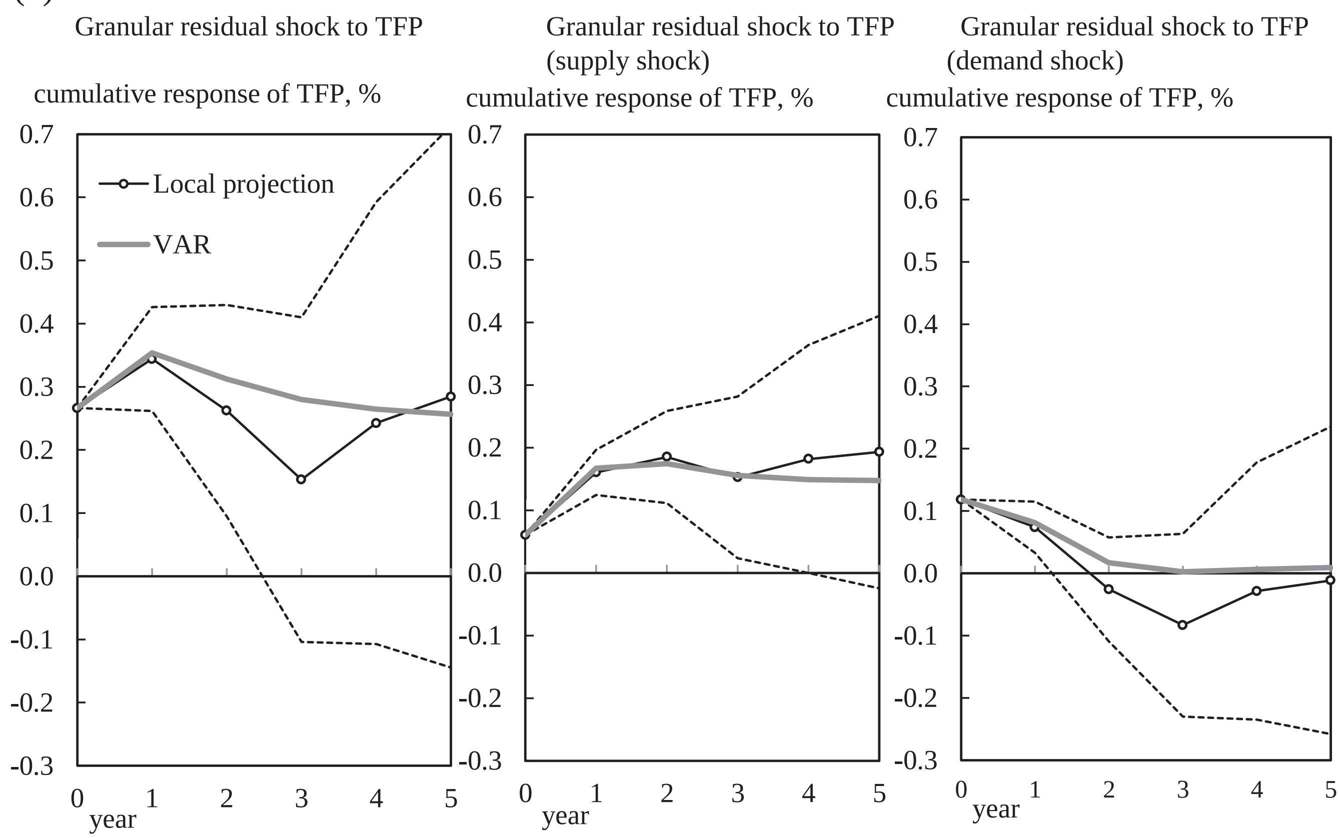


Figure 16: Local Projection (+1σ Cumulative Responses)

(1) Japan



(2) U.S.



Note: Dotted lines indicates plus minus 1 sigma bands of the cumulative impulse responses.