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# Innovation and product reallocation in the great recession☆

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ABSTRACT

We use detailed product- and firm-level data to study the sources of innovation and the patterns of productivity growth over the period from 2007 to 2013. We document several new facts on product reallocation. First, every quarter around 8 percent of products are reallocated in the economy, and the entry and exit of products are prevalent among different types of firms. Second, most reallocation of products occurs within the boundaries of the firm. The entries and exits of firms only make a small contribution in the overall creation and destruction of products. Third, product reallocation is strongly pro-cyclical and declined by more than 25 percent during the Great Recession. This cyclical pattern is almost entirely explained by a decline in within firm reallocation. Motivated by these facts, we study the causes and consequences of reallocation within incumbent firms. As predicted by Schumpeterian growth theories, the rate of product reallocation strongly depends on the innovation efforts of the firms and has important implications for revenue growth, improvements in products' quality, and productivity dynamics. Our estimates suggest that the decline in product reallocation through these margins has contributed greatly to the slow growth experienced after the Great Recession.



## 1. Introduction

For decades, economists have identified product entry and exit as one of the key mechanism through which product innovation translates into economic growth (Aghion et al., 2014; Aghion and Howitt, 1992; Grossman and Helpman, 1991). But despite the important theoretical implications of product innovation, little is known empirically about the process of the creation and destruction of a product, and how this process differs across different types of firms. In this paper, we study product reallocation across and within producers and how it evolved during the Great Recession. What is the role of product reallocation on output growth and quality improvements in the recent decade? How sensitive is innovation by new firms, small incumbents, and large incumbents to changes in aggregate economic conditions? New evidence on these questions will shed light on how resources are allocated to their best use within an economy and inform the recent debate on the sources of productivity slowdown in the US (Davis and Haltiwanger, 2014; Decker et al., 2014).

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We begin by assessing the magnitude of product creation and destruction in the consumer goods sector over the period from 2007Q1 to 2013Q4. We use detailed product- and firm-level data at the barcode level and find that new products are systematically displacing existing products in the market. In our data set, a 12-digit number called the Universal Product Code (UPC) uniquely identifies each product, which is the finest level of disaggregation at the product level. Under this definition, firms reallocate more than 8 percent of the products in the economy every quarter. In this setting reallocation results from both the introduction of new products and the destruction of existing products. This is particularly relevant for large and well-diversified firms that sell products in several product categories. Consistent with several theories of creative destruction, we find that firms expanding, as well as firms contracting, contribute to the overall destruction of products. This source of dynamism in the US economy occurs within the boundaries of the firm, and as the result of the entries and exits of new firms. We find that most product reallocation is made by surviving incumbent firm that add or drop products in their portfolios.

After establishing the magnitude and pervasiveness of the reallocation of products, we evaluate the evolution during and after the Great Recession. We find that product reallocation is strongly pro-cyclical; the quarterly reallocation rate declined by more than 25 percent during the Great Recession. To better understand the sources of the cyclicality in the reallocation rate we decompose it in a within and a between firms component. We find that the cyclical pattern is overwhelmingly a consequence of within firm reallocation. In particular, most of the decline in reallocation within firms resulted from the decline in the creation of products during the recession.

In the second part of the paper we provide evidence that the decline in dynamism in the product market affected the economic growth and recovery after the Great Recession. Schumpeterian growth models have traditionally linked the speed of product reallocation to the innovation efforts of firms and to subsequent gains in productivity. To uncover the causes and consequences of the reallocation slowdown, we begin by establishing that the speed of product reallocation is strongly related to the innovation efforts of the firms as captured by their expenditures on research and development. This is consistent with theories featuring creative destruction where new and better varieties replace obsolete ones.

We then establish the relation between product reallocation and several innovation outputs such as revenue growth, improvements in products quality, and productivity growth. To do so, we follow Akcigit and Kerr (2010) and distinguish between two different types of innovation from the perspective of the firms: incremental innovations and extensions. Incremental innovations represent new products within the existing product lines of the firms, where they can use their capabilities and resources and benefit from economies of scale or scope. Extensions represent products outside the main business line of the firm. They are less common than incremental innovations because they represent larger innovations, which are likely to be more costly to develop. We find that incremental innovations have an immediate large impact on revenue. Extensions, on the other hand, are in general more innovative new products launched with higher average quality and have a higher impact on the total factor productivity (TFP) of the firm. In a similar way, we divide product exits into two types: products that are more likely to be terminated due to creative destruction (replaced by new products within the same product category) and those that were phased out due to the scaling down of firms' operations (products without replacement). Consistent with Schumpeterian theories[1], exits due to creative destruction are correlated with gains in TFP. Overall, we find that firms that have higher reallocation rates grow faster, launch products with higher average quality, and experience larger gains in productivity. Our evidence indicates that the decline in reallocation during the recession can explain around 15 percent of the drop in aggregate productivity in this period and had substantial implications for economic growth in the years that followed.

For most of our analysis, we rely primarily on the Nielsen Retail Measurement Services (RMS) scanner data set. It consists of more than 100 billion observations of weekly prices, quantities, and store information of approximately 1.4 million products identified at the UPC level. We combine the information on prices with the weight and volume of the product to compute unit values in order to approximate the quality of each product. In addition, we identify the firm owning each UPC by obtaining information from GS1, the single official source of barcodes in the United States. Our combined data set provides the revenue, price, quantity, and the quality for each product in a firm's portfolio and allows us to study how the within and between margins of product entry and exit evolve over time. Furthermore, we complement these data with measures of TFP and research and development expenses from Compustat. To the best of our knowledge, our paper is the first one to link the product-level information available in the Nielsen RMS with firm-level observables available in other data sets.

Our paper contributes to several active research areas. Despite the vast theoretical implications of product reallocation, the empirical analysis on the aggregate behavior of product reallocation lags far behind its theoretical counterpart due to data limitations. The literature on reallocation has focused on the input markets by using establishment and labor market data (Davis and Haltiwanger, 1992; Foster et al., 2001; 2006). By contrast, we focus on the reallocation in output markets. Importantly, we study the relative contribution of incumbents to the aggregate reallocation rate without inferring it from their job flow information.

Few papers have studied the degree of product reallocation directly. Bernard et al. (2010) study the extent of product switching within firms by using production classification codes (five-digit SIC codes), and Bernard and Okubo (2016) studies the role of product adding and dropping within Japanese manufacturing firms by using six-digit products according to the

[1] See Aghion et al. (2014) for more detail.

Japanese Standard Industrial Classification. Given the level of aggregation of their data, several firms could produce the same product. We substantially improve on this data by measuring products at a much finer level by using scanner data. With these data, we can explore the dynamics of each firms' unique portfolio of products as opposed to studying the dynamics of their product lines.

Our work is also closely related to Broda and Weinstein (2010) who study the patterns of product entry and exit using a similar data set to ours. But, they collect data from consumers rather than stores. Collecting data at the store level offers the advantage of observing, for the categories available, the entire universe of products for which a transaction is recorded in a given week rather than the products consumed by a sample of households. Therefore, with our data set, we can cover less frequently consumed goods and can provide less noisy measures of the entry and exit of products. Our paper builds on their work by examining between and within firm reallocation separately and by examining the contribution of each of these components during the Great Recession. Moreover, we examine the reallocation patterns of firms by subdividing them into several different dimensions: according to their size, their level of diversification (i.e., firms selling in a single product category versus firms selling in multiple product categories) and whether they are expanding or contracting at a given point in time.

Furthermore, by studying the connection between reallocation and different measures of innovation, our work links studies on reallocation that focus mainly on moving resources from less to more efficient uses to enhance productivity growth to the parallel literature on innovation (Acemoglu et al., 2013; Akcigit and Kerr, 2010; Garcia-Macia et al., 2016; Klette and Kortum, 2004; Lentz and Mortensen, 2008). Although we examine only the retail sector of the economy, to the best of our knowledge, our paper is the first to empirically establish the relation between product entry and exit and the innovation activities of a firm. In particular, we can empirically test and validate several predictions of Schumpeterian growth models with our matched data set; predictions that have been hard to examine in the past due to data availability issues.

Our work is also related to the literature on firm dynamics that studies the propagation of aggregate shocks after large contractions in output (Caballero and Hammour, 1994; Moreira, 2016). We find that both the reallocation rate and the entry rate of products suffered a persistent decline after the Great Recession. The decline in product creation had consequences in terms of revenue for the firms in the short run. But, more importantly, this missing generation of products, in the spirit of Gourio and Siemer (2014), combined with the evidence we provide on the relation between reallocation and productivity growth, can have substantial implications for the slow recovery experienced by the US economy in the years following the Great Recession.

Further, our paper complements the growing literature on how business formation and product creation amplifies business cycles (Bilbiie et al., 2012; Chatterjee and Cooper, 1993; Jaimovich and Floetotto, 2008; Minniti and Turino, 2013). Our estimations can be used to discipline the parameters these models use to replicate the number of firms and products at different stages in the business cycle. More importantly, the evidence we present emphasizes the endogenous interaction between the innovation efforts of firms, their product scope, and outcomes such as revenue and productivity. Our work highlights the importance of multiproduct firms in business cycle modeling and the role of firms heterogeneity in understanding the degree to which macroeconomic shocks propagate in the economy.

The rest of the paper is organized as follows. Section 2 presents the data and describes our procedure to link our product-level data set with the firm-level information available in Compustat. In Section 3, we define reallocation and provide several decompositions to explore the relative contributions of the between and within margins. In this section we also provide an interpretation of the magnitudes of the reallocation rate we observe and describe its evolution during the Great Recession. In Section 5 we examine the possible determinants of relocation. We examine its relation with R&D and define incremental innovations and extensions along with exits due to creative destruction and terminations due to firms scaling down their operations. Section 6 tests and validates the predictions of the models involving creative destruction and shows the relations between reallocation and revenue growth, quality improvements, and productivity dynamics. Section 7 concludes. We include several robustness tests and additional empirical findings in the appendix.

## 2. Data description

### *2.1. Baseline product-level dataset*

We rely primarily on the Nielsen Retail Measurement Services (RMS) scanner data set that is provided by the Kilts–Nielsen Data Center at the University of Chicago Booth School of Business. The RMS consists of more than 100 billion unique observations at the week × store × UPC level. Each individual store reports weekly prices and quantities of every UPC code that had any sales volume during that week.[2]

[2] In comparison to other scanner data sets collected at the store level, the RMS covers a much wider range of products and stores. Table G.I in the appendix shows that in comparison to the IRI Symphony data set, a similar data set widely used in the academic literature, the RMS covers 14 times more products in a given year. In terms of revenue the RMS represents roughly 2 percent of total household consumption whereas the IRI Symphony is 30 times smaller. In comparison to scanner data sets collected at the household level, the RMS also has a wider range of products because it reflects the universe of transactions for the categories it covers as opposed to the purchases of a sample of households. The Nielsen Homescan, for example, that contains information on the purchases of 40,000–60,000 US households covers less than 60% of the products the RMS covers in a given year.

The data is generated by point-of-sale systems and contains approximately 40,000 distinct stores from 90 retail chains across 371 MSAs and 2500 counties between January 2006 and December 2014. The data set comprises around 12 billion transactions per year worth, on average, $220 billion. Over our sample period the total sales across all retail establishments are worth approximately $2 trillion and represent 53% of all sales in grocery stores, 55% in drug stores, 32% in mass merchandisers, 2% in convenience stores, and 1% in liquor stores.

The baseline data consist of approximately 1.64 million distinct products identified by UPC. The data is organized into 1070 detailed product modules that are aggregated into 114 product groups that are then grouped into 10 major departments.[3] For example, a 31-ounce bag of Tide Pods has UPC 037000930389 and is produced by Procter & Gamble and is mapped to product module "Detergent-Packaged" in product group "Detergent", which belongs to the "Non-Food Grocery" department. Each UPC contains information on the brand, size, packaging, and a rich set of product features. We use the weight and the volume of the product to compute unit values.

Our data set combines all sales at the national and quarterly level, although we also conduct some exercises at the annual frequency given that some firm-level observables are only available at that frequency. For each product $j$ in quarter $t$, we define revenue $r_{jt}$ as the total revenue across all stores and weeks in the quarter. Likewise, quantity $q_{jt}$ is defined as total quantities sold across all stores and weeks in the quarter. Price $p_{jt}$ is defined by the ratio of revenue to quantity, which is equivalent to the quantity weighted average price.

A critical part of our analysis is the identification of entries and exits. For each product we use the panel structure to identify the entry and exit periods. In addition, we follow Broda and Weinstein (2010) and Argente and Yeh (2017) and use the UPC as the main product identifier. This is because it is rare that a meaningful quality change occurs without resulting in a UPC change. A concern that can arise from this assumption is that a new UPC might not always represent a new product. For instance, Chevalier et al. (2003) notes that some UPCs might get discontinued only to have the same product appear with a new UPC. This is not a concern in our data set because Nielsen detects these UPCs and assigns them their prior UPC.

We define entry as the first quarter of sales of a product and exit as the quarter after we last observe a product being sold. To study the patterns in the entry and exit rates, we use information for all products in the period from 2007Q1 to 2013Q4, that include cohorts born from 2007Q1 to 2013Q4 and cohorts born before that period, from whom we cannot determine the cohort and age.[4] In addition, given that our estimates of products entries and exits might be affected by the entries and exits of stores in the sample, we consider only a balanced sample of stores during our sample period.

In order to minimize concerns of potential measurement error in the calculation of a products entry and exit, our baseline sample excludes private label products, considers products with at least one transaction per quarter after entering, and excludes products in the Alcohol and General Merchandise departments. We exclude private label goods because, in order to protect the identity of the retailer, Nielsen alters the UPCs associated with private label goods. As a result, multiple private label items are mapped to a single UPC that makes it difficult to interpret the entry and exit patterns of these items since it is not possible to determine the producer of these goods. We consider products without missing quarters to rule out the possibility that our results are driven by seasonal products, promotional items, or products with very small revenue. And, finally, we exclude the two departments for which the coverage in our data is smaller and less likely to be representative.

Our final sample is described in Table 1. On average, more than 222,000 distinct UPCs are present in our sample each year. Most products have revenue of less than $10,000 per quarter but 2.4% of the products make more than $1 million. A product module contains approximately 242 products, a product group 2486 products, and a department 25,688 products on average. The table shows that these numbers remain very stable before, during, and after the Great Recession.

Nonetheless, all of the results that follow are robust to using the full sample of products that are available in the RMS. We present these results in Appendix G. Lastly, Appendix G also includes results where, instead of using the barcode as the main product identifier, we identify products using a broader definition using the product attributes provided by Nielsen as in Kaplan and Menzio (2015). Under this alternative definition, a good is the same if it shares the same observable features, the same size, and the same brand, but may have different UPCs. We use this definition to minimize the concern that new products, when identified by their UPCs, represent only marginal innovations from the perspective of the firms. Under this definition, each new entry represents at least a new product line for the firm. Appendix G shows that the results we describe below on the aggregate reallocation rate and on the impact of product reallocation on several innovation outputs remain very similar under this specification.

### 2.2. Matching firm and products

We link firms and products with information obtained from GS1 US, the single official source of UPCs. In order to obtain a UPC, firms must first obtain a GS1 company prefix. The prefix is a five- to ten-digit number that identifies firms and their products in over 100 countries where the GS1 is present. The number of digits in a company prefix indicates different

[3] The ten major departments are: Health and Beauty aids, Dry Grocery (e.g., baby food, canned vegetables), Frozen Foods, Dairy, Deli, Packaged Meat, Fresh Produce, Non-Food Grocery, Alcohol, and General Merchandise).

[4] Note that we excluded the first four and last four quarters of the sample. Because we define entry as the first quarter of sales of a product and exit as the first quarter after we last observe a product being sold, we could identify an abnormally high entry in the first quarters and abnormally high exit in the last quarters. Our procedure ensures that we only classify a product as entering if it was not observed for at least a full year before, and a product as exiting if we no longer observe it for at least a full year past exit.

**Table 1**
Summary statistics of products and firms.
The table reports summary statistics of products and firms included in the baseline sample. The variables are defined at the quarter level and grouped as averages for the period 2007Q1–2013Q4, and for the subperiods 2007Q1–2007Q4, 2010Q1–2010Q4, and 2013Q1–2013Q4. "Entrants" refers to the average share of products and firms that are identified for the first time in the data set in each quarter. "Exits" refers to the average share of products and firms that are identified for the last time in the data set in each quarter. "Continuers expanding (contracting)" refers to firms that had products in the previous quarter and are increasing (decreasing) the number of products. The diversification statistics report the average number of products and the share of firms within each categories. The revenue is the total sales (in dollars) across all stores and weeks of the quarter, deflated by the Consumer Price Index for All Urban Consumers. The revenue presents the share of products and firms in each revenue interval and is computed using all surviving products and continuing firms.

| | | | 2007–2013 | 2007 | 2010 | 2013 |
|---|---|---|---|---|---|---|
| Average # of products | | | 222,105 | 211,101 | 214,001 | 252,189 |
| Share of products by status | Entrants | | 0.043 | 0.047 | 0.037 | 0.047 |
| | Exits | | 0.036 | 0.046 | 0.033 | 0.030 |
| # of products by diversification | Per module | | 242 | 234 | 232 | 272 |
| | Per group | | 2486 | 2356 | 2391 | 2836 |
| | Per department | | 25,688 | 24,348 | 24,709 | 29,304 |
| Share of products by revenue | $[0, 10^4]$ | | 0.610 | 0.626 | 0.605 | 0.615 |
| | $[10^4, 10^5]$ | | 0.230 | 0.223 | 0.232 | 0.228 |
| | $[10^5, 10^6]$ | | 0.136 | 0.128 | 0.138 | 0.135 |
| | $>=10^6$ | | 0.024 | 0.023 | 0.025 | 0.022 |
| Average # of firms | | | 12,861 | 13,074 | 12,361 | 13,319 |
| Share of firms by status | Entrants | | 0.021 | 0.025 | 0.017 | 0.024 |
| | Exits | | 0.020 | 0.023 | 0.018 | 0.019 |
| | Continuers expanding | | 0.122 | 0.118 | 0.110 | 0.141 |
| | Continuers contracting | | 0.128 | 0.145 | 0.125 | 0.118 |
| Share of firms by diversification | Single product | Share of firms | 0.262 | 0.280 | 0.265 | 0.252 |
| | Multi-product & single module | Share of firms | 0.259 | 0.256 | 0.261 | 0.257 |
| | | Average # of products | 5.7 | 5.6 | 5.6 | 5.7 |
| | Multi-module & single group | Share of firms | 0.126 | 0.121 | 0.126 | 0.128 |
| | | Average # of products | 12.9 | 12.5 | 13.2 | 12.9 |
| | Multi-group & single department | Share of firms | 0.192 | 0.187 | 0.191 | 0.195 |
| | | Average # of products | 23.5 | 22.4 | 24.4 | 23.8 |
| | Multi-department | Share of firms | 0.161 | 0.155 | 0.157 | 0.168 |
| | | Average # of products | 61.6 | 56.9 | 59.4 | 65.4 |
| Share of continuing firms by revenue | $[0,10^4]$ | | 0.462 | 0.480 | 0.455 | 0.462 |
| | $[10^4, 10^5]$ | | 0.262 | 0.256 | 0.265 | 0.264 |
| | $[10^5, 10^6]$ | | 0.182 | 0.177 | 0.185 | 0.180 |
| | $>=10^6$ | | 0.093 | 0.087 | 0.095 | 0.094 |

capacities for firms to create UPCs. For example, a ten-digit prefix allows firms to create ten unique UPCs, and a six-digit prefix allows them to create up to 100,000 unique UPCs. Although the majority of firms own a single prefix, it is not rare to find that some own several. Small firms, for example, often obtain a larger prefix first, which is usually cheaper, before expanding and requesting a shorter prefix.[5] Larger firms, on the other hand, usually own several company prefixes due to past mergers and acquisitions. For example, Procter & Gamble owns the prefixes of firms it acquired such as Old Spice, Folgers, and Gillette. For consistency, in what follows we perform the analysis at the parent company level.

Given that the GS1 US data contains all of the company prefixes generated in the US, we combine these prefixes with the UPC codes in the RMS.[6] With this data set, we can compute the revenue, price, quantity, and quality of each product in a firm's portfolio to study how the within and between margins of product creation and destruction evolve over time.

Table 1 describes the characteristics of the firms in our data. We have a yearly average of 12,861 firms with slightly more firms present after the recession. Similar to the size distribution of products, the size distribution of firms is fat-tailed.[7] In addition, most firms are well diversified: 26% of the firms own a single product, 26% are multi-product firms that belong to a single module, 13% are multi-module firms that belong to a single product group, 19% sell in multiple product groups but in a single department, and 16% are multi-department firms.

### *2.3. Matching Nielsen RMS and Compustat*

For the later analysis, we obtain firm-level characteristics from Compustat. To combine the Nielsen data with the Compustat database, we match the names in the GS1 to those in Compustat using a string matching algorithm that is described

[5] Previous studies, including Broda and Weinstein (2010), have assumed that the first six digits of the UPC identify the manufacturing firm. This assumption is valid for 93% of the products in our sample.

[6] Less than 5 percent of the UPCs belong to prefixes not generated in the US. We were not able to find a firm identifier for those products.

[7] Table G.II in the appendix shows the top 20 firms in terms of revenue in our data. The top 10 firms alone account for approximately 27% of the total revenue.

in Schoenle (2017). After applying the algorithm, we match 479 publicly traded firms over our sample period.[8] Our matched sample represents 22% of the total sales in Compustat and 45% of the total revenue in the RMS. Approximately 21% of the total number of products in the data belong to publicly traded firms. We describe in detail the construction of firm-level variables in Appendix D and the summary statistics in Table G.III in the appendix.

## 3. Reallocation of products

### 3.1. Measurement of reallocation

In this section we document several new stylized facts on the level and evolution of product creation, destruction, and reallocation in the U.S. consumer goods sector. We start with a description of the measures that we use to identify the aggregate levels and cyclical patterns of product reallocation. Most products' entries and exits do not necessarily translate into entry and exit of firms because the majority of products are produced by multi-product firms (Table 1). In order to study the degree of heterogeneity in this sector, we also compute the firm-specific reallocation rates for products.

*Aggregate reallocation.* To capture the importance of product entry and exit, we use information on the number of new products, the number of exits of products, and the total number of products for each firm $i$ over time $t$, and define the aggregate entry and exit rates as follows:

$$n_t = \frac{\sum_i N_{it}}{\sum_i T_{it}} \tag{1}$$

$$x_t = \frac{\sum_i X_{it}}{\sum_i T_{it-1}} \tag{2}$$

where $N_{it}$, $X_{it}$, and $T_{it}$ are the numbers of entering products, exiting products, and total products, respectively. The entry rate is defined as the number of new products in period $t$ as a share of the total number of products in period $t$. The exit rate is defined as the number of products that exited in period $t$ (i.e., the last time we observe a transaction was in $t-1$) as a share of the total number of products in period $t-1$.[9]

Two relations link these concepts: the net growth rate of the stock of available products equals the entry rate minus the exit rate; the overall change in the portfolio of products available to consumers can be captured by the sum of the entry and exit rates. We refer to this last concept as the product reallocation rate, in particular:

$$r_t = n_t + x_t \tag{3}$$

With this rate we can measure the extent of the changes in the status of a product in our data, either from the entry or the exit margin.

*Average within firm reallocation.* Using information on the numbers of entering products, exiting products, and total products by each firm $i$ over time $t$, we can define the average reallocation of products by firms as the (unweighted) mean entry and exit rates across all firms as follows:

$$\bar{n}_t = \frac{1}{\gamma_t} \sum_{i=1} n_{it} \tag{4}$$

$$\bar{x}_t = \frac{1}{\gamma_{t-1}} \sum_{i=1} x_{it} \tag{5}$$

where $n_{it} = \frac{N_{it}}{T_{it}}$, $x_{it} = \frac{X_{it}}{T_{it-1}}$, and $\gamma_t$ is the number of firms active in $t$. The average reallocation rate of firms is then defined as:

$$\bar{r}_t = \bar{n}_t + \bar{x}_t \tag{6}$$

*Aggregated and average within firm reallocation.* The aggregate level of reallocation and the average level within can be easily related following the Olley and Pakes decomposition. The aggregate reallocation rate is composed of the average reallocation and a component that measures the covariance between the market share and reallocation rates:

$$r_t = \bar{r}_t + \sum_{i \in \Gamma_t} (r_{it} - \bar{r}_t)(t_{it} - \bar{t}_t) \tag{7}$$

where $t_{it} = \frac{T_{it}}{\sum_i T_{it}}$ measures the product share of firm $i$ at $t$, $t_{it} \geq 0$ and sums to one; and $\Gamma_t$ is the set of active firms in $t$. The second component of the decomposition captures whether firms with more products are more likely to be those with high or low reallocation rates.

[8] A few public firms in our sample are conglomerates combining more than one independent corporation. For the later analysis, we combine their information into a single firm to perform our reduced-form analysis at the public firm level.

[9] The main advantage of assigning a product exit to the quarter following the last observed transaction of a product is that we can define relative changes in the stock of products as the difference between entry and exit rate.

**Table 2**
Aggregate and average within entry, exit, and reallocation rates.
The table reports the aggregate and average entry, exit, and reallocation rates, as defined in Section 3.1, for the baseline sample. The entry, exit, and reallocation rates are computed at the quarter level, seasonally adjusted, and then grouped as averages for the periods 2007Q1–2013Q4, and for the subperiods 2007Q1–2007Q4, 2010Q1–2010Q4, and 2013Q1–2013Q4.

| | | All 2007–2013 | (1) 2007 | (2) 2010 | (3) 2013 | Change (2)/(1)-1 | (3)/(2)-1 |
|---|---|---|---|---|---|---|---|
| Aggregate rates | Reallocation | 0.079 | 0.094 | 0.070 | 0.078 | −25% | 11% |
| | Entry | 0.043 | 0.047 | 0.037 | 0.047 | −21% | 25% |
| | Exit | 0.036 | 0.046 | 0.033 | 0.031 | −30% | −5% |
| Average within rates | Reallocation | 0.108 | 0.125 | 0.095 | 0.113 | −24% | 19% |
| | Entry | 0.055 | 0.061 | 0.047 | 0.065 | −22% | 37% |
| | Exit | 0.056 | 0.068 | 0.050 | 0.051 | −27% | 3% |

### *3.2. Magnitude and heterogeneity of product reallocation*

The rates of aggregate product creation and destruction are remarkably large. Table 2 shows that, on average, 8 percent of all products are reallocated every quarter in the period from 2007 to 2013. This amount means that about one in three products are either destroyed or created over a typical 12-month interval. This fact highlights the fluidity in the consumer goods sector.

The level of reallocation depends on the product definition. In our baseline sample, products are defined at the UPC level for a set of consumer goods industries that excludes generics, alcohol, and general merchandise. In the alternative sample, where both generics and general merchandise are included, we observe an average quarterly reallocation rate of 7.6 percent, which is very close to the 7.9 percent that we observe in the baseline sample. The alternative sample, for the same universe of goods, but for the more coarse definition of product (as defined at the level of different module and brand), we still find an average quarterly reallocation rate of 4.7 percent. This percentage means that while some creations and destructions of products might involve small changes in their characteristics, a big share of reallocation happens with the creation and destruction of new brands.

Our measures of product reallocation can be compared with measures of reallocation at the production unit level and input level. Using data from Business Dynamics Statistics, we compute analogous measures of firm reallocation using information on the entries and exits of establishments. We find that, during the same period, the entries and exits of establishments are about 20 percent of total establishments over a one-year period. The reallocation of establishments weighted by employment is about 9 percent per year. In our dataset, we observe entry and exit of firms of about 17 percent over a one-year period, which is similar to the whole economy's reallocation of firms. Foster et al. (2016) find that the evolution of job reallocation, computed as defined by Davis et al. (1996), points to an average level of about 13 percent a quarter over the period from 2006 to 2012.

Over the 2007 to 2013 period, the quarterly entry rate of products was 4.3 percent, and the quarterly exit rate was 3.6 percent. These rates mean that over a typical 12-month interval, about one in five new products are created in these sectors, and about one in six are no longer available (Table 2). Overall, while the growth rate of products in the consumer goods sector increased almost 1 percent per quarter over this period, both the entry and exit margins are important in explaining the changes in the portfolio of products available to consumers.

To better understand the sources of reallocation, we examine the degree of heterogeneity in the firm-specific reallocation of products. Table 2 shows the average quarterly reallocation, entry, and exit rates for the period from 2007 to 2013. On average, firms in the consumer goods industry add or drop about 10.8 percent of the products in their portfolios. The fact that this rate is larger than the aggregate reallocation rate means a negative covariance exists between reallocation rates and product shares, that is, firms that produce a lower number of products have, on average, higher reallocation rates. This negative covariance is driven entirely by the entries and exits of firms. Most products are produced by multi-product firms, and thus the entries and exits of firms only account for a small share of product reallocation (only 1 out of 20 products are created and destroyed by entering or exiting firms).

Over the period from 2007 to 2013, the average firm-specific quarterly entry rate of products was 5.5 percent, and the average quarterly exit rate was 5.6 percent. We classify firms by their net creation of products (expanding, contracting, and unchanged), and access to the market (entering, exiting, and incumbent).[10] Overall, most additions of products are made by expanding firms and most product destructions are made by contracting firms. Table 3 shows that expanding firms add around one product out of every three (one out of every four if we exclude entering firms). As expected, firms that are reducing the total number of products on net are adding products at a smaller rate (only about 1.3 percent, on average). Expanding firms destroy products at a rate of about 2 percent, while firms that are destroying products on net phase out about 33.6 percent of their products (23.4 percent when we exclude exiting firms).

[10] Appendix B provides details on the disaggregation.

**Table 3**
Average within reallocation rates by types of firms.
The table reports the average entry, exit, and reallocation firm-specific rates by types of firms, as defined in Section 3.1, for the baseline sample. The entry, exit, and reallocation rates are computed for different sets of firms at the quarter level, seasonally adjusted, and then grouped as averages for the period 2007Q1–2013Q4, and for the subperiods 2007Q1–2007Q4, 2010Q1–2010Q4, and 2013Q1–2013Q4.

| | All 2007–2013 | (1) 2007 | (2) 2010 | (3) 2013 | Change (2)/(1)-1 | (3)-(2)-1 |
|---|---|---|---|---|---|---|
| Reallocation | | | | | | |
| Expanding entrant | 1.000 | 1.000 | 1.000 | 1.000 | 0% | 0% |
| Expanding incumbent | 0.256 | 0.267 | 0.250 | 0.261 | −6% | 4% |
| Contracting exit | 1.000 | 1.000 | 1.000 | 1.000 | 0% | 0% |
| Contracting incumbent | 0.246 | 0.276 | 0.235 | 0.235 | −15% | 0% |
| Unchanged incumbent | 0.006 | 0.009 | 0.004 | 0.006 | −51% | 41% |
| Entry | | | | | | |
| Expanding entrant | 1.000 | 1.000 | 1.000 | 1.000 | 0% | 0% |
| Expanding incumbent | 0.237 | 0.243 | 0.234 | 0.244 | −4% | 4% |
| Contracting incumbent | 0.013 | 0.018 | 0.011 | 0.013 | −39% | 20% |
| Unchanged incumbent | 0.003 | 0.004 | 0.002 | 0.003 | −51% | 41% |
| Exit | | | | | | |
| Expanding incumbent | 0.019 | 0.024 | 0.017 | 0.018 | −31% | 6% |
| Contracting exit | 1.000 | 1.000 | 1.000 | 1.000 | 0% | 0% |
| Contracting incumbent | 0.234 | 0.259 | 0.225 | 0.223 | −13% | −1% |
| Unchanged incumbent | 0.003 | 0.004 | 0.002 | 0.003 | −51% | 41% |
| Reallocation | | | | | | |
| Q1 revenue | 0.173 | 0.209 | 0.150 | 0.183 | −28% | 22% |
| Q2 revenue | 0.098 | 0.096 | 0.089 | 0.108 | −7% | 22% |
| Q3 revenue | 0.086 | 0.091 | 0.078 | 0.092 | −14% | 18% |
| Q4 revenue | 0.075 | 0.084 | 0.069 | 0.075 | −18% | 9% |
| Entry | | | | | | |
| Q1 revenue | 0.084 | 0.090 | 0.072 | 0.107 | −20% | 48% |
| Q2 revenue | 0.049 | 0.050 | 0.042 | 0.061 | −16% | 45% |
| Q3 revenue | 0.046 | 0.050 | 0.039 | 0.054 | −22% | 37% |
| Q4 revenue | 0.043 | 0.049 | 0.039 | 0.044 | −20% | 11% |
| Exit | | | | | | |
| Q1 revenue | 0.102 | 0.135 | 0.088 | 0.089 | −35% | 2% |
| Q2 revenue | 0.051 | 0.048 | 0.049 | 0.050 | 2% | 3% |
| Q3 revenue | 0.041 | 0.042 | 0.040 | 0.040 | −5% | 1% |
| Q4 revenue | 0.032 | 0.035 | 0.030 | 0.032 | −15% | 7% |
| Reallocation | | | | | | |
| Single-product | 0.112 | 0.137 | 0.098 | 0.110 | −28% | 13% |
| Single-module | 0.070 | 0.078 | 0.060 | 0.075 | −23% | 25% |
| Single-group | 0.081 | 0.095 | 0.072 | 0.080 | −24% | 11% |
| Single-department | 0.072 | 0.085 | 0.065 | 0.072 | −24% | 11% |
| Multi-department | 0.080 | 0.095 | 0.069 | 0.080 | −28% | 17% |
| Entry | | | | | | |
| Single-product | 0.027 | 0.034 | 0.021 | 0.033 | −39% | 61% |
| Single-module | 0.024 | 0.026 | 0.020 | 0.030 | −23% | 51% |
| Single-group | 0.031 | 0.033 | 0.028 | 0.034 | −16% | 21% |
| Single-department | 0.029 | 0.033 | 0.026 | 0.034 | −22% | 31% |
| Multi-department | 0.035 | 0.039 | 0.028 | 0.039 | −26% | 39% |
| Exit | | | | | | |
| Single-product | 0.087 | 0.107 | 0.079 | 0.080 | −26% | 1% |
| Single-module | 0.046 | 0.053 | 0.041 | 0.046 | −23% | 12% |
| Single-group | 0.051 | 0.062 | 0.045 | 0.047 | −28% | 5% |
| Single-department | 0.043 | 0.053 | 0.039 | 0.039 | −26% | −1% |
| Multi-department | 0.045 | 0.057 | 0.040 | 0.041 | −29% | 1% |

There is substantial heterogeneity in the size of firms that produce consumer goods. We classify firms by their quartile of revenue, and we measure the contribution of each group to the aggregate reallocation. When we exclude entrants and exits, the average reallocation rates among incumbent firms by revenue quartile are slightly larger among high revenue firms, which hold several products on average, and thus an overwhelmingly large share of products created or destroyed every quarter originate in firms in the top quartile of the distribution of revenue.

Another important source of heterogeneity in this industry is the degree of diversification of products between firms (Table 1). Single-product firms have higher rates of product reallocation because they are also more likely to be entering or exiting firms. When we exclude single-product firms, diversified firms (in particular, multi-department firms) have slightly larger average rates of reallocation, and thus diversified firms make a higher contribution to the aggregate reallocation of products (Table 3).

### 3.3. Evolution of product reallocation in the Great Recession

After examining the sources of heterogeneity in the product reallocation rates, we analyze the evolution of our measures of product reallocation over the business cycle. The main takeaway from this analysis is that the reallocation of products in the period under analysis is very pro-cyclical. The share of products that were created or destroyed was approximately 9.4 percent on average during 2007, dropping to about 7.0 percent on average during 2010, and recovering to 7.8 percent three years later (Table 2).

A significant fraction of this cyclical component is explained by the variation in the number of new products that firms created during the Great Recession. The quarterly entry rate declines from around 4.7 percent to about 3.7 percent in the period from 2007 to 2010, followed by a full recovery by 2013. The aggregate exit rate trends downwards during this period and the deviations from trend are also pro-cyclical. The aggregate quarterly exit rate varies from 4.6 percent to 3.3 percent from 2007 to 2010, followed by a decline until the end of 2013.

This evolution contrasts with the evidence in Broda and Weinstein (2010). Their period of analysis includes the 2001 recession and they find that the aggregate creation of products is pro-cyclical, while the aggregate product destruction is countercyclical, although the magnitude of the latter is quantitatively less important. This pattern indicated that product reallocation was only slightly pro-cyclical. We find the same strong pro-cyclicality in the entries of new products but we do not find any evidence of counter-cyclicality in the exit rate. Our findings differ from those in Aghion et al. (2017) who report countercyclical product churn after using data from the US Census of Manufacturers. Because the US Census of Manufacturers is only available in years ending in 2 and 7, their measure can only capture a period of recession followed by a recovery and is unlikely to capture product dynamics occurring during the Great Recession. Our findings of a strong decline in product reallocation during the Great Recession and the subsequent slow recovery are similar to the evolution of job creation and destruction documented in Foster et al. (2001). In the Great Recession, job creation fell by as much or more than the increase in job destruction. In this respect, the Great Recession was not a time of increased reallocation. These patterns also contrast with the responsiveness of job creation and destruction in prior recessions. In prior recessions, periods of economic contraction had a sharp increase in job destruction and a mild decrease in job creation.[11]

The aggregate cyclical patterns of the product reallocation rates are pervasive across different types of firms. We find that during our period of analysis, the strong decline in the reallocation rates during the Great Recession is present across all types of firms. Nonetheless, we also find some evidence of systematic heterogeneity as some firms are more procyclical than others. The decline in average reallocation in 2008 and 2009 was larger among firms that reduced their stock of products; such decline results from decreases in both entry rates and exit rates (Table 2). When we sort all firms based on quartiles of revenue, we find that all quartiles experience a decline in product reallocation during the Great Recession that is mostly explained by the evolution of the rate at which firms create products. The decline in reallocation was particularly large among low revenue firms and resulted from the decline in both entry rates and in exit rates. We also find, however, that after the Great Recession the product reallocation rates of the lower quartile of revenue show a greater rebound. The cyclical evolution of the product reallocation rates for both diversified and undiversified firms is similar over the period, and does not exhibit substantial differences.

## 4. Decomposition of reallocation

Next, we apply decomposition methods to shed further light on the evolution of our product reallocation measures and explain what economic forces drive the evolution of this rate. The literature that examines the aggregate productivity in the economy has developed decomposition methods to investigate the sources of productivity change. Aggregate productivity is typically computed as a weighted average of productivity at the producer level. Because the productivity levels of producers are heterogenous, aggregate productivity changes over time can reflect both shifts in the distribution of producer-level productivity and changes in the composition of firms. In turn, changes in the composition of firms in the economy can result not only from changes in market shares among surviving firms, but also from the entry of new producers and the exit of old ones. These three sources of changes in the composition are often named the effect of reallocation of producers in the economy.

We borrow from this literature and apply these methods to our setting. Our goal is to decompose changes in the aggregate rate of product reallocation between changes in the re-allocative behavior of firms and changes in the distribution of firms. The idea is that product reallocation can evolve both because the incumbent firms change their behavior or because firms enter and exit markets. In our case, incumbent firms can increase the rate at which they add or destroy products, while their share of products varies over time, that is, firms that reallocate more might be gaining or losing overall market share. We use these methods to identify the main sources that explain the decline in reallocation during the Great Recession and in the post-recession period.

[11] As highlighted in Davis et al. (1996), the greater responsiveness of job destruction relative to job creation in these earlier cyclical downturns means that recessions are times of increased reallocation.

*4.1. Decomposing changes in reallocation: Accounting for entry and exit of firms*

Using Eq. 7, we can decompose the changes in reallocation between quarter $t$ and a reference quarter 0, $\Delta r_{t,0} = r_t - r_0$, as follows:

$$\Delta r_{t,0} = \bar{r}_t - \bar{r}_0 + \sum_{i\in\Gamma_t}(r_{it} - \bar{r}_t)(t_{it} - \bar{t}_t) - \sum_{i\in\Gamma_0}(r_{i0} - \bar{r}_0)(t_{i0} - \bar{t}_0)$$

where $t_{ik} = \frac{T_{ik}}{\sum_i T_{ik}}$ measures the product share of firm $i$ in quarter $k$, $t_{ik} \geq 0$ and sums to 1, and $\Gamma_k$ is the set of active firms in $k$, $k = t, 0$. After simplifying the notation, we express this decomposition in the following components:

$$\Delta r_{t,0} = \Delta\bar{r}_{t,0} + \Delta\sum_{i\in\Gamma_t}(r_{it} - \bar{r}_t)(t_{it} - \bar{t}_t) \tag{8}$$

The first component represents changes in the average reallocation rate within firm, and the second component is the adjustment by differences in size across firms. Thus, the evolution in reallocation rates of products can come from changes in the average within firm reallocation rate, and changes in the distribution of products across firms that reallocate more or less intensively.

Melitz and Polanec (2015) proposed an extension of the Olley and Pakes decomposition to accommodate entry and exit of firms, such that we can separately obtain the contribution of continuing, entering and exiting firms. The underlying idea is that we can write the change in reallocation rates as:

$$\begin{aligned}\Delta r_{t,0} = {} & \bar{r}_t^{C_{t,0}} - \bar{r}_0^{C_{t,0}} + \sum_{i\in C_{t,0}}(r_{it} - \bar{r}_t)(t_{it} - \bar{t}_t) - \sum_{i\in C_{t,0}}(r_{i0} - \bar{r}_0)(t_{i0} - \bar{t}_0)\\ & + \sum_{i\in EN_{t,0}} t_{it}\left(\sum_{i\in EN_{t,0}}\frac{t_{it}}{\sum_{i\in EN_{t,0}} t_{it}}r_{it} - \sum_{i\in C_{t,0}}\frac{t_{it}}{\sum_{i\in C_{t,0}} t_{it}}r_{it}\right)\\ & - \sum_{i\in EX_{t,0}} t_{i0}\left(\sum_{i\in EX_{t,0}}\frac{t_{i0}}{\sum_{i\in EX_{t,0}} t_{i0}}r_{i0} - \sum_{i\in C_{t,0}}\frac{t_{i0}}{\sum_{i\in C_{t,0}} t_{i0}}r_{i0}\right)\end{aligned} \tag{9}$$

where the contribution of each firm to the aggregate change in the reallocation rate is separated into three categories for continuing $C_{t,0}$, entering $EN_{t,0}$ and exiting $EX_{t,0}$ firms. The first terms of the decomposition apply the Olley and Pakes decomposition to the subset of surviving firms, that is decomposed between the change in the average reallocation rate among continuing firms and the change in the covariance between the product share and the reallocation rate. The latter two terms measure the contribution of entry and exit of firms to the aggregate change in the reallocation rates. The entry component is defined as the weighted average difference between the reallocation rate of entrants and reallocation rate of continuers. The exit component is defined as the weighted average difference between the reallocation rate of exit firms and reallocation rate of continuers.

An alternative approach to identify the importance of the different margins that can potentially generate changes in the aggregate product reallocation is to explore the equality $r_t = \sum_{i\in\Gamma_t} r_{it}t_{it}$, and we can write the changes as

$$\Delta r_{t,0} = \sum_{i\in C_{t,0}}(r_{it}t_{it} - r_{i0}t_{i0}) + \sum_{i\in EN_{t,0}} r_{it}t_{it} - \sum_{i\in EX_{t,0}} r_{i0}t_{i0}$$

For continuing firms, we can further disentangle between the sum of the changes in the reallocation rate, holding firms' shares of the product market constant (within-firm component), and the percentage sum of shares changes holding all firms' entry constant (between-firm component). The decomposition will be then:

$$\Delta r_{t,0} = \sum_{i\in C_{t,0}} t_{i0}(r_{it} - r_{i0}) + \sum_{i\in C_{t,0}} r_{it}(t_{it} - t_{i0}) + \sum_{i\in EN_{t,0}} r_{it}t_{it} - \sum_{i\in EX_{t,0}} r_{i0}t_{i0} \tag{10}$$

For continuing firms, the first component captures changes in the reallocation rate within them, while the second captures the contribution of changes in product shares between them. Griliches and Regev (1995) redefines the decomposition above such that the average aggregate reallocation rate is the reference $\bar{r}_{0,t} = \frac{r_0+r_t}{2}$. The decomposition is then given by

$$\Delta r_{t,0} = \sum_{i\in C_{t,0}} t_{it}(r_{it} - \bar{r}_{0,t}) - \sum_{i\in C_{t,0}} t_{0,t}(r_{i0} - \bar{r}_{t0}) + \sum_{i\in EN_{t,0}} t_{it}(r_{it} - \bar{r}_{0,t}) - \sum_{i\in EX_{t,0}} t_{i0}(r_{i0} - \bar{r}_{0,t})$$

And we can split the contribution of continuing firms between within and between components as follows

$$\Delta r_{t,0} = \sum_{i\in C_{t,0}} \bar{t}_{i,0t}(r_{it} - r_{i0}) + \sum_{i\in C_{t,0}} (\bar{r}_{i,0t} - \bar{r}_{0,t})(t_{it} - t_{i0}) + \sum_{i\in EN_{t,0}} t_{it}(r_{it} - \bar{r}_{0,t}) - \sum_{i\in EX_{t,0}} t_{i0}(r_{i0} - \bar{r}_{0,t}) \tag{11}$$

where $\bar{r}_{i,0t} = \frac{r_{i0}+r_{it}}{2}$ and $\bar{t}_{i,0t} = \frac{t_{i0}+t_{it}}{2}$. The contribution of the within-firm component among surviving firms is now weighted by the average product share of each firm, while the between-firm contribution is weighted by the average reallocation rate.

**Table 4**
Decomposition.
The table reports decomposition exercises on the change in the aggregate entry, exit, and reallocation rates by types of firms, as defined in Section 4. We decompose the first differences of the aggregate entry and exit rates. The decomposed series are seasonally adjust and then summed over the periods 2007Q1–2009Q4, and 2010Q1–2012Q4. The decomposition of the reallocation rate is computed by adding the subcomponents of the entry and exit decompositions.

| | | Within (+) | Between (+) | Cross (+) | Entry (+) | Exit (−) | Change |
|---|---|---|---|---|---|---|---|
| OP - Non-dynamic | | | | | | | |
| Entry rate | | | | | | | |
| | 07Q1–09Q4 | −2.9 | 1.0 | – | – | – | −1.9 |
| | 10Q1–12Q4 | 2.2 | −1.0 | – | – | – | 1.2 |
| Exit rate | | | | | | | |
| | 07Q1–09Q4 | −2.4 | 0.7 | – | – | – | −1.7 |
| | 10Q1–12Q4 | −0.3 | −0.2 | – | – | – | −0.5 |
| Reallocation rate | | | | | | | |
| | 07Q1–09Q4 | −5.3 | 1.6 | – | – | – | −3.6 |
| | 10Q1–12Q4 | 1.8 | −1.2 | – | – | – | 0.7 |
| OP - Dynamic | | | | | | | |
| Entry rate | | | | | | | |
| | 07Q1–09Q4 | −23.4 | 18.7 | – | 3.1 | 0.2 | −1.9 |
| | 10Q1–12Q4 | −19.2 | 17.5 | – | 3.0 | 0.1 | 1.2 |
| Exit rate | | | | | | | |
| | 07Q1–09Q4 | 19.5 | −19.1 | – | 0.2 | 2.2 | −1.7 |
| | 10Q1–12Q4 | 18.4 | −17.3 | – | 0.1 | 1.7 | −0.5 |
| Reallocation rate | | | | | | | |
| | 07Q1–09Q4 | −4.0 | −0.4 | – | 3.1 | 2.2 | −3.6 |
| | 10Q1–12Q4 | −0.8 | 0.2 | – | 3.0 | 1.7 | 0.7 |
| GR | | | | | | | |
| Entry rate | | | | | | | |
| | 07Q1–09Q4 | −8.1 | 3.3 | | 3.0 | 0.2 | −1.9 |
| | 10Q1–12Q4 | −5.6 | 3.9 | | 3.0 | 0.1 | 1.2 |
| Exit rate | | | | | | | |
| | 07Q1–09Q4 | 4.1 | −3.7 | | 0.2 | 2.2 | −1.7 |
| | 10Q1–12Q4 | 3.8 | −2.7 | | 0.1 | 1.7 | −0.5 |
| Reallocation rate | | | | | | | |
| | 07Q1–09Q4 | −4.0 | −0.4 | – | 3.0 | 2.2 | −3.6 |
| | 10Q1–12Q4 | −1.8 | 1.2 | – | 3.0 | 1.7 | 0.7 |
| FHK | | | | | | | |
| Entry rate | | | | | | | |
| | 07Q1–09Q4 | −10.4 | 1.0 | 4.7 | 3.0 | 0.2 | −1.9 |
| | 10Q1–12Q4 | −8.1 | 1.3 | 5.1 | 3.0 | 0.1 | 1.2 |
| Exit rate | | | | | | | |
| | 07Q1–09Q4 | 2.4 | −5.4 | 3.3 | 0.2 | 2.2 | −1.7 |
| | 10Q1–12Q4 | 2.6 | −3.9 | 2.5 | 0.1 | 1.7 | −0.5 |
| Reallocation rate | | | | | | | |
| | 07Q1–09Q4 | −8.0 | −4.4 | 8.0 | 3.0 | 2.2 | −3.6 |
| | 10Q1–12Q4 | −5.5 | −2.6 | 7.5 | 3.0 | 1.7 | 0.7 |

The main advantage of this last decomposition is that the contribution of entrants can now be negative, and the contribution of exits can be positive.

Foster et al. (2001) proposes a slightly modified decomposition, where the reference level is period 0 instead of a time varying average. This approach facilitates comparisons across different time periods. The third contribution of the surviving firms is the cross-firm component, that captures the covariance between the change in the share of products and the change in entry rate. The decomposition is then given by

$$\begin{aligned}\Delta r_{t,0} = &\sum_{i \in C_{t,0}} t_{i0}(r_{it} - r_{i0}) + \sum_{i \in C_{t,0}} (r_{i0} - r_0)(t_{it} - t_{i0}) + \sum_{i \in C_{t,0}} (r_{it} - r_{i0})(t_{it} - t_{i0}) \\ &+ \sum_{i \in EN_{t,0}} t_{it}(r_{it} - r_0) - \sum_{i \in EX_{t,0}} t_{i0}(r_{i0} - r_0)\end{aligned} \tag{12}$$

Similar to the decomposition above, the contribution of entry and exit can be negative or positive, depending on how the reallocation rates among entrants and exiters compare with the reallocation rate in the baseline period 0.

### *4.2. Results*

Table 4 reports the results of the decompositions. We apply them to changes in the aggregate entry, exit, and reallocation rates. In particular, we report the decomposition for the Great Recession by adding the cumulative one-quarter changes between 2007Q1 and 2009Q4 and for the period following the Great Recession by adding the cumulative one-quarter changes between 2010Q1 and 2012Q4.[12]

First, we present the results for the method developed by Olley and Pakes (1996). This method does not accommodate firm entry and exit but is used as a reference and baseline for the other methods. During the Great Recession, the weighted average reallocation rate declines by around 3.6 percentage points, and is decomposed into a change of −5.3 percentage points in the first moment of firms' reallocation distribution (the unweighted mean), and an increase of 1.6 percentage points in the joint distribution of reallocation and market shares (the covariance between reallocation and product shares). This means that the Great Recession saw a substantial decline in the average reallocation rates, and that firms reallocating more were increasing their product share relative to firms reallocating less. In the post-recession period, the aggregate reallocation increased by 0.7 percentage points as a result of a recovery of 1.8 percentage points in the average reallocation of firms, and a 1.2 percentage point decline in the covariance between product shares and reallocation.

Next, we implement the methodology developed by Melitz and Polanec (2015) to further understand the contributions of the entries and exits of firms to product reallocation rates. The results show that the decline in the average product reallocation rate during the Great Recession was partially offset by a 0.9 percentage points increase in the reallocation rate from net entry of firms (which in its turn is further decomposed into 3.1 percentage points stemming from the entry of products from entering firms, and −2.2 percentage points explained by the exit of products from exiting firms). In the period following the Great Recession, net entry contributed 1.3 percentage points to the recovery in the aggregate product reallocation rates.[13] The contribution of the net entry of firms in the recession and post-recovery periods is positive and very similar, which indicates that the distinct evolution of the reallocation in those periods was mainly driven by surviving incumbents firms, which seems to be the group that was more dynamic in adjusting their re-allocative behavior.

When we adapt the standard within and between decompositions to the product reallocation rate, we obtain similar results for the impact of entry and exit of firms. The Griliches and Regev (1995) decomposition shows that the decline in reallocation in the recession period results in −4.0 percentage points decline in the rate of product reallocation within surviving firms and −0.4 percentage points from variation between surviving firms. This decomposition indicates that there is almost not between effect, that is, the market share of high reallocation firms is very similar. In the post-recession period the within component is −1.8 percentage points, while the between amounts to 1.2 percentage points. Comparing the results for the two periods shows that both components recovered. The Foster et al. (2001) decomposition assigns a larger negative contribution to the within component (−8.0 percentage points), a larger negative component to the between firms reallocation (−4.4 percentage points), and a sizable positive cross effect (8.0 percentage points). This decomposition allows a clear counterfactual exercise where changes in reallocation rates are calculated holding constant the product shares at their initial levels. The above findings suggest that the smaller effect of within and between firms variation in explaining the decline in reallocation can result from the cross-term, i.e. the relation between the change in shares and the change in reallocation rates.

Overall, the findings from this section show that the aggregate reallocation rate is largely explained by the decisions by incumbents firms to create and destroy products, followed by the contributions of entering and exiting firms. Moreover, the decompositions show that the decline in aggregate reallocation in the recession resulted largely from declines in reallocation within surviving firms. Further, Table 4 shows that these conclusions are robust to the choice of decomposition method.

These results motivate us to better understand the consequences of reallocation within incumbent firms. We interpret these empirical facts as evidence that some of the variation in the productivity and growth within surviving firms that Foster et al. (2008) find is related to how they manage heterogenous multi-product portfolios that are comprised of winners (high revenue and high productivity products) and losers (low revenue and low productivity).

## 5. Product reallocation and innovation

What does product reallocation represent? In most models of creative destruction, output reallocation plays an important role in determining productivity dynamics. These models emphasize that adopting new products inherently involves the destruction of the old ones and that the pace at which this destruction takes place depends crucially on the innovation activities of the firm.[14] In this section we establish that there is a positive relationship between product reallocation and innovation.

### *5.1. Exploring heterogeneous types of entry and exit*

The results of the previous section do not distinguish products being added or destroyed in what regards to how innovative they are. When we observe an entry of a new UPC, it might be a good that is very similar to others that the firm

[12] The two periods correspond to a 12-quarter (3-year) overall change. We select these particular dates to match the overall evolution that we observe for the aggregate reallocation.

[13] It is worth pointing out that the sign of the contribution of entry is always positive and the size of exit is always negative, given that the reallocation rates of entering and exiting firms are by definition equal to 1, while for surviving firms is closer to the level of 0.1.

[14] For example, in Aghion and Howitt (1992) firms get monopoly rents for their innovations until the next innovation arrives. In this case, the incentives for investing in innovation are substantial.

**Table 5**
Summary statistics for aggregate and within entry and exit rates by types.
The table reports aggregate and average within firm entry and firm exit rates by different types of products. "Entry Improvement" rate is defined as the share of total products created within the firms' previous portfolio of modules. "Entry Extensions" rate is the share of total products created outside a firm's previous portfolio of modules. "Entry firm" refers to the ratio of new products by new firms relative to the total products. "Exit Improvement" rate is the share of total products eliminated within firm's previous portfolio of modules. "Exit Extensions" rate is the share of total products exiting that eliminated modules from a firm's portfolio. "Exit firm" refers to the share of firms that exit the market. The rates are computed at the quarter level, seasonally adjusted, and then grouped as averages for the period 2007Q1–2013Q4, and for the subperiods 2007Q1–2007Q4, 2010Q1–2010Q4, and 2013Q1–2013Q4.

| | | All 2007–2013 | (1) 2007 | (2) 2010 | (3) 2013 | Change (2)/(1)-1 | (3)-(2)-1 |
|---|---|---|---|---|---|---|---|
| i. Aggregate rates | | | | | | | |
| Entry | | | | | | | |
| | Improvement | 0.036 | 0.039 | 0.031 | 0.038 | −20% | 22% |
| | Extension | 0.005 | 0.005 | 0.004 | 0.005 | −26% | 40% |
| | Firm | 0.003 | 0.003 | 0.002 | 0.003 | −27% | 36% |
| | ALL | 0.043 | 0.047 | 0.037 | 0.047 | −21% | 25% |
| Exit | | | | | | | |
| | Improvement | 0.030 | 0.038 | 0.027 | 0.025 | −29% | −7% |
| | Extension | 0.005 | 0.006 | 0.004 | 0.004 | −35% | −3% |
| | Firm | 0.002 | 0.002 | 0.001 | 0.002 | −29% | 11% |
| | ALL | 0.036 | 0.046 | 0.033 | 0.031 | −30% | −5% |
| ii. Average within rates | | | | | | | |
| Entry | | | | | | | |
| | Improvement | 0.024 | 0.025 | 0.022 | 0.028 | −15% | 30% |
| | Extension | 0.009 | 0.010 | 0.008 | 0.012 | −22% | 50% |
| | Firm | 0.022 | 0.025 | 0.018 | 0.025 | −30% | 41% |
| | ALL | 0.055 | 0.061 | 0.047 | 0.065 | −22% | 37% |
| Exit | | | | | | | |
| | Improvement | 0.020 | 0.023 | 0.018 | 0.018 | −21% | 2% |
| | Extension | 0.016 | 0.022 | 0.014 | 0.013 | −35% | −6% |
| | Firm | 0.020 | 0.024 | 0.018 | 0.020 | −24% | 10% |
| | ALL | 0.056 | 0.068 | 0.050 | 0.051 | −27% | 3% |

already has in its portfolio, or a good that is truly unique and innovative. As discussed in Section 2 defining a product as a unique UPC can cause some measurement concerns. In our data set, small changes in packing or volume likely result in a new bar code.[15] This type of new product is not what researchers have in mind when developing models of the effect of innovation in reallocation. We address this issue in two ways. First, we distinguish between two different types of innovation – incremental and extensions– and we examine their evolution in the recession and post-recession periods. Second, we show that the results reported in the previous sections do not qualitatively change when we consider coarser definitions of products.

Under the first approach, our goal is to distinguish between the entry of a new product within the main product line and a new product that is beyond the main product line of the firm. New products that constitute only marginal changes in the stock of existing products, such as changes in volume and other minor characteristics of the products, are unlikely to involve a lot of resources when developed or to have significant impact on the outcomes of the firm. By contrast, new products that are not within the core business of the firm are likely to involve substantial changes in the production technology with sizable consequences to the outcomes of the firm. We implement a distinction between types of product by using the classification system in the Nielsen data set. In particular, we classify a new product at $t$ as an improvement if the firm already has other products of that type, that is, if the firm at $t-1$ already produces goods in the same module as the product being created. We classify a new product as an extension if it is in a new module for the firm.

We apply the same principle to classify exits by type. Exits are classified as improvements if the firm maintains operations in that module. Exits are classified as extensions if they correspond to a cessation of activity in that module. The distinction shows if some products are terminated due to creative destruction (replaced by new products within the same product category) and those that are phased out due to the scaling down of the firms operations (products without replacement).

Table 5 presents the decomposition of aggregated and average entry and exit rates by type over the period under analysis. For comparison, we also show the share of entering and exiting products introduced by entering and exiting firms. As expected, most changes in UPCs occur within the same product module: around 80 percent of entering and exiting UPCs.

[15] Broda and Weinstein (2010) also acknowledge that the their measures of product creation and destruction include changes in characteristics that might be secondary and use information on the UPC's characteristics to show that only a small part results from changes in size and flavor. We follow an alternative approach that fits better with our overall goal.

**Table 6**
Reallocation activities and R&D expenses.
The table reports the coefficients of OLS regressions with revenue weights. The dependent variable reallocation at $t$, defined as the product entry rate plus the product exit rate, at the firm level as defined in the main text. The main independent variable is the ratio of R&D expenses to total sales at $t-1$. The construction of the rest of the control variables is described in Appendix D. Other controls include firm fixed-effects and year fixed-effects. Revenue is winsorized at the 1% level. The sample used include the set of publicly traded firms that are found in the Nielsen RMS. Standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

| Dep. var.: $r_{f,t+1}$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| R&D | 0.668* | 0.625* | 0.873** | 0.872** |
| | (0.363) | (0.363) | (0.392) | (0.392) |
| Size | 0.006 | 0.014 | 0.014 | 0.015 |
| | (0.032) | (0.033) | (0.035) | (0.035) |
| Price cost margin | | 0.344 | 0.405* | 0.399* |
| | | (0.210) | (0.224) | (0.226) |
| Std. sale | | | −0.169 | −0.161 |
| | | | (0.127) | (0.127) |
| Kaplan–Zingales | | | | 0.000 |
| | | | | (0.001) |
| Observations | 661 | 661 | 599 | 595 |
| R-squared | 0.563 | 0.565 | 0.576 | 0.579 |
| Year effects | Yes | Yes | Yes | Yes |
| Firm effects | Yes | Yes | Yes | Yes |

Product extensions correspond to 11 percent of all entries, and exit extensions correspond to 14 percent of all exits. Over the period under analysis, we observe that product extensions and shut downs of product lines are only slightly more cyclical than the entrants and exits of within firm's product lines. We interpret this as evidence that over the business cycle, firms change the rate at which they make marginal changes in their stock of products, as well as the introduction of new product lines.

### 5.2. Research and development expenses

In order to further understand the relation between firms' innovation activities on the reallocation of their products, we use the various measures of product creation and destruction described in the previous section along with information on R&D expenses available in Compustat. This measure is particularly relevant because, as it is defined by Compustat, it encompasses all planned search aimed at the discovery of new knowledge that could lead to new products or the improvement of the existing ones.

Given that our main interest is to explore the determinants of reallocation within incumbent firms, we focus on studying firms present in every period in our sample. Our specification is the following:

$$r_{f,t+1} = \alpha + \beta R\&D_{f,t} + \Gamma X_{f,t} + \mu_f + \lambda_t + \epsilon_{f,t} \quad (13)$$

where $r_{f,\,t}$ represents the reallocation rate of firm $f$ in year $t$. R&D represents the ratio of research and development expenses to total sales for firm $f$ at time $t$. Our main focus is on $\beta$ that captures the direct impact of R&D on product reallocation. $X_{f,\,t}$ is a vector of firm-level controls that vary over time. All our specifications include year fixed effects, $\lambda_t$, to control for possible trends and firm fixed effects, $\mu_f$, to control for other types of heterogeneity.

Table 6 shows the results. Column (1) shows that R&D expenditures have a large positive impact on reallocation after controlling for firm size because larger firms tend to engage in more R&D activities. Next, we add a wide range of controls to disentangle the effect of R&D from potentially confounding firm-level factors. In column (2) we include the price cost margin and in column (3) a control for firm idiosyncratic volatility. Our results do not vary under these specifications or if measures of financial constraints are included (column (4)). This is not surprising given that even without any time varying control the inclusion of both firm and time fixed effects account for most of the possible variation. In all cases the point estimates are large and statistically significant; a hypothetical increase in R&D expenditures relative to sales of 1 percentage point increases the reallocation rate by 0.6–0.9 percentage points. This is equivalent to an increase of close to 10% in the reallocation rate.[16]

[16] In the Appendix E, we test a placebo specification by using future R&D expenditures instead of past R&D expenditures in predicting the change in the reallocation rate, and rule out a concern about confounding factors, such as time-varying firm-level shocks.

**Table 7**
Reallocation activities and revenue growth.
The table reports the coefficients of OLS regressions with revenue weights. The dependent variable is the revenue growth in the next quarter. The reallocation rate at $t$ of firm $f$, $r_{f,\,t}$, is defined as the product entry rate plus the product exit rate at the firm level as defined in the main text. Revenue is winsorized at the 1% level. Standard errors are presented in parentheses. $^{***}$, $^{**}$, and $^{*}$ represent statistical significance at 1%, 5%, and 10% levels, respectively.

| Dep. var.: Revenue$_{f,t+1}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $r_{f,\,t}$ | 0.2869$^{***}$ | | | | | | |
| | (0.011) | | | | | | |
| $n_{f,\,t}$ | | 0.5281$^{***}$ | | | | | |
| | | (0.014) | | | | | |
| $n_{f,\,t}$ (in module) | | | 0.5445$^{***}$ | | | | |
| | | | (0.017) | | | | |
| $n_{f,\,t}$ (beyond module) | | | | 0.5452$^{***}$ | | | |
| | | | | (0.028) | | | |
| $x_{f,\,t}$ | | | | | −0.7333$^{***}$ | | |
| | | | | | (0.017) | | |
| $x_{f,\,t}$ (in module) | | | | | | −0.0396$^{*}$ | |
| | | | | | | (0.023) | |
| $x_{f,\,t}$ (beyond module) | | | | | | | −1.7489$^{***}$ |
| | | | | | | | (0.027) |
| Revenue$_{f,\,t}$ | 0.8007$^{***}$ | 0.7976$^{***}$ | 0.7972$^{***}$ | 0.7989$^{***}$ | 0.7554$^{***}$ | 0.7565$^{***}$ | 0.7598$^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 242,660 | 242,803 | 242,803 | 242,803 | 242,711 | 242,711 | 242,711 |
| R-squared | 0.970 | 0.970 | 0.970 | 0.970 | 0.967 | 0.967 | 0.967 |
| Year Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

## 6. Reallocation and growth of firm

Our findings so far strongly suggest that the innovation efforts of the firms are associated with higher reallocation rates. The second key prediction of Schumpeterian growth models to test is whether increases in the reallocation rates of products lead to larger growth rates for firms and to improvements in the products they produce.

### 6.1. Reallocation and revenue growth

We first confirm the prediction on revenue growth by estimating the following equation in the data:

$$\text{Revenue}_{f,t+1} = \alpha + \beta\, r_{f,t} + \Gamma X_{f,t} + \mu_f + \lambda_t + \epsilon_{f,t} \tag{14}$$

where Revenue$_{f,\,t}$ is the sum of the revenue of all products in the firm's portfolio at time $t$. As before, all our specifications include both firm and time fixed effects and consider only a balanced sample of firms. Furthermore, given that in order to run this specification we only require the information available in the RMS, Eq. (14) is estimated using quarterly data.

Column (1) in Table 7 shows that $\beta$, our coefficient of interest, is both economically and statistically significant. This is after controlling for revenue in the previous period. The table also shows that, not surprisingly, most of the revenue growth due to reallocation of products comes from the entry margin. The exit rate on the other hand is negatively related to the revenue growth in the next quarter.

At the entry margin, the entry of products in the module where a firm operated before, Column (3) in the table, and the entry of products in a new module, Column (4), are associated with revenue growth by similar magnitudes. At the exit margin, closing down a product module completely, Column (7), is more strongly correlated with revenue growth, compared to destroying products in the module they keep operating in (Column (6)).

### 6.2. Reallocation and quality improvements

A similar analysis can be done to explore whether higher reallocation rates lead to increases in the average quality of firms' portfolios. Several growth models, such as those in Klette and Kortum (2004) and Lentz and Mortensen (2008), predict that higher quality versions of a product are the outcome of the innovation activities of the firms. To study these predictions, we use a measure to proxy for product quality based on relative price.

**Benchmark quality** To measure a product's average quarterly quality at the firm level, we use prices to approximate quality as in Argente and Lee (2016). This measure is similar to those used in the international trade literature where, if a sector or firm in a country is able to export a large volume at a high price, then it must be producing high-quality goods (Hallak and Schott, 2011; Hummels and Klenow, 2005; Kugler and Verhoogen, 2012). As a benchmark measure, we represent quality with the average relative price of the UPC-level good within each product category. First, we measure the

**Table 8**
Reallocation activities and benchmark quality improvement.
The table reports the coefficients of OLS regressions with revenue weights. The dependent variable is the improvement in benchmark quality in the next quarter. Reallocation rate at $t$ of firm $f$, $r_{f,t}$, is defined as the product entry rate plus the product exit rate at the firm level as defined in the main text. Revenue is winsorized at the 1% level. Standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

| Dep. var.: $Q^{\text{benchmark}}_{f,t+1}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $r_{f,t}$ | 0.0255*** | | | | | | |
| | (0.004) | | | | | | |
| $n_{f,t}$ | | 0.0383*** | | | | | |
| | | (0.005) | | | | | |
| $n_{f,t}$ (in module) | | | 0.0295*** | | | | |
| | | | (0.006) | | | | |
| $n_{f,t}$ (beyond module) | | | | 0.0617*** | | | |
| | | | | (0.009) | | | |
| $x_{f,t}$ | | | | | 0.0144** | | |
| | | | | | (0.006) | | |
| $x_{f,t}$ (in module) | | | | | | −0.0043 | |
| | | | | | | (0.007) | |
| $x_{f,t}$ (beyond module) | | | | | | | 0.0446*** |
| | | | | | | | (0.009) |
| Revenue$_{f,t}$ | 0.0064*** | 0.0059*** | 0.0059*** | 0.0060*** | 0.0064*** | 0.0064*** | 0.0064*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 242,537 | 242,679 | 242,679 | 242,679 | 242,588 | 242,588 | 242,588 |
| R-squared | 0.925 | 0.924 | 0.924 | 0.924 | 0.924 | 0.924 | 0.924 |
| Year Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

log-difference between the price of good $j$ and the median price for category $c$ in quarter $t$.

$$R^{\text{benchmark}}_{jt} = \log \frac{P_{jt}}{\bar{P}_{ct}}$$

where $R^{\text{benchmark}}_{jt}$ is the relative price, and $\bar{P}_{ct}$ is the median price of category $c$. Therefore, if the price of a high quality type of milk, say organic milk, is much higher than the median price of milk, then $R^{\text{benchmark}}_{jt}$ is positive and high.

We then calculate the firm-level average quality by combining information on product-level quality and on the product portfolio of each firm. The average product quality of firm $f$ is:

$$Q^{\text{benchmark}}_{ft} = \sum_{jf} \omega_{jft} R^{\text{benchmark}}_{jt}$$

where $\omega_{jft}$ is a revenue weight. $Q^{\text{benchmark}}_{ft}$ captures how far the prices of the products produced by firm $f$ are from the median price level in each of their categories at time $t$.

Using these quality measures, we now test the association between our measure of product reallocation and improvement in the average quality of the product at the firm level. We use the following specification:

$$Q_{f,t+1} = \alpha + \beta\, r_{f,t} + \Gamma X_{f,t} + \mu_f + \lambda_t + \epsilon_{f,t} \tag{15}$$

where $f$ is the firm, and $t$ is the quarter. Our main focus is on $\beta$ that captures the direct impact of reallocation on firm-level average quality in the next quarter. $X_{f,t}$ is a vector of firm-level controls, $\mu_f$ represents firm fixed effects, and $\lambda_t$ represents time fixed effects. By construction, the benchmark quality measure is centered at zero and the percentile-based quality measure is center at 50. Table 8 reports the relation between our reallocation measures and our benchmark quality measure, $Q^{\text{benchmark}}_{f,t+1}$. We again keep a balanced panel of firms to investigate the importance of reallocation among surviving firms. An increase in reallocation is associated with quality improvements in the following quarter. This correlation is mainly driven by the entry margin of products. Large firms tend to produce higher quality products on average. Furthermore, as shown in columns (3) and (4), quality improves more for product extensions beyond the module than for incremental innovations.

### 6.3. Reallocation and productivity

The remaining central implication of models with creative destruction to be tested is whether the reallocation of products is a major source of productivity growth. This prediction has been hard to examine directly in the data given the lack of availability of data sets combining both product- and firm-level information.[17]

[17] This question has been, nonetheless, explored in other contexts such as the reallocation of establishments (Bartelsman and Doms, 2000; Foster et al., 2016; 2001). In both cases, a large share of productivity growth can be explained by the reallocation of resources.

**Table 9**
Reallocation activities and firm-level productivity.
The table reports the coefficients of OLS regressions with revenue weights. The dependent variable is the natural logarithm of the total factor productivity at the firm-level at $t+1$. Reallocation at $t$ is defined as the product entry rate plus the product exit rate at the firm level as defined in the main text. The construction of the control variables is described in Appendix D. Other controls include firm fixed-effects and year fixed-effects. Revenue is winsorized at the 1% level. The sample used include the set of publicly traded firms that are found in the Nielsen RMS. Standard errors are presented in parentheses. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

| $TFP_{f,t+1}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| $r_{f,t}$ | 0.360*** | 0.371*** | 0.358*** | 0.357*** | | | | | | |
| | (0.103) | (0.103) | (0.105) | (0.106) | | | | | | |
| $n_{f,t}$ | | | | | 0.026 | | | | | |
| | | | | | (0.119) | | | | | |
| $n_{f,t}$ (in module) | | | | | | −0.063 | | | | |
| | | | | | | (0.121) | | | | |
| $n_{f,t}$ (beyond module) | | | | | | | 1.894*** | | | |
| | | | | | | | (0.559) | | | |
| $x_{f,t}$ | | | | | | | | 0.916*** | | |
| | | | | | | | | (0.175) | | |
| $x_{f,t}$ (in module) | | | | | | | | | 0.966*** | |
| | | | | | | | | | (0.182) | |
| $x_{f,t}$ (beyond module) | | | | | | | | | | 0.247 |
| | | | | | | | | | | (0.723) |
| Size | 0.172*** | 0.155*** | 0.198*** | 0.199*** | 0.224*** | 0.224*** | 0.224*** | 0.203*** | 0.200*** | 0.225*** |
| | (0.032) | (0.034) | (0.035) | (0.035) | (0.033) | (0.032) | (0.032) | (0.034) | (0.034) | (0.033) |
| Price Cost Margin | | −0.301 | −0.405* | −0.383* | −0.773*** | −0.762*** | −0.760*** | −0.319 | −0.324 | −0.767*** |
| | | (0.196) | (0.223) | (0.227) | (0.216) | (0.216) | (0.214) | (0.224) | (0.224) | (0.215) |
| Std. Sale | | | −0.289** | −0.277** | −0.246** | −0.249** | −0.241** | −0.287** | −0.291** | −0.246** |
| | | | (0.119) | (0.120) | (0.118) | (0.118) | (0.117) | (0.118) | (0.118) | (0.118) |
| Kaplan–Zingales | | | | 0.000 | −0.000 | −0.000 | −0.000 | 0.000 | 0.000 | −0.000 |
| | | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 834 | 834 | 777 | 773 | 865 | 865 | 865 | 773 | 773 | 865 |
| R-squared | 0.859 | 0.859 | 0.866 | 0.866 | 0.848 | 0.848 | 0.850 | 0.869 | 0.870 | 0.848 |
| Year Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

We begin by computing total factor productivity in the Compustat data relying on the methodology developed by İmrohoroğlu and Tüzel (2014). We then regress the natural logarithm of TFP on the annual reallocation rate as follows:

$$TFP_{f,t+1} = \alpha + \beta\, r_{f,t} + \Gamma X_{f,t} + \mu_f + \lambda_t + \epsilon_{f,t} \tag{16}$$

where as before $f$ is the firm, and $t$ is the year. Our main focus is once again on $\beta$ which captures the direct impact of reallocation on firm's productivity. Table 9 reports our results. Column (1) shows that both variables are strongly correlated even after controlling for the size of the firm. This is important because in general larger firms have higher productivity and, as we have shown, they also have higher rates of reallocation. Column (2) includes controls for market power by including the price-to-cost margin as control. Column (3) includes the standard deviation of sales to control for the possibility that firms with faster sales growth have higher rates of product entry and exit. Lastly, in column (4) we control for differences in financial constraints across firms by including the Kaplan–Zingales index. Our estimates of $\beta$ remain similar across specifications and show that, on average, an increase of 1 percentage point in reallocation increases TFP around 0.35%.[18]

When we examine the contribution of entries and exits separately, we find that the contribution of reallocation to TFP mainly comes from exits. But, interestingly, when we explore improvements and extensions separately, we find that product extensions, products that are more likely to involve larger innovations, have a positive and significant contribution to TFP. On the other hand, exits within the main module of the firm, those that are more likely to come from replacing outdated products for better products, contribute positively and significantly to TFP.

### 6.4. Discussion

The importance of product reallocation has been central in models of creative destruction for decades but, as the theoretical literature evolved, lack of data availability made many of its central implications hard to test. Our calculations validate many predictions of these models. First, we find that faster innovation-led growth is associated with higher rates of reallocation of products (Aghion et al., 2014). Product reallocation is positively related to R&D and to revenue growth. Second, although both entrants and incumbents innovate (Bartelsman and Doms, 2000), most growth appears to come from incumbents improving on existing varieties (Acemoglu and Cao, 2015; Garcia-Macia et al., 2016). Third, small firms and new

[18] In the Appendix E, we test a placebo specification using past TFP instead of future TFP as an outcome variable.

**Table 10**
Correlation between reallocation activities and employment growth rates.
The table shows the correlation between the reallocation activities and the employment growth rates from the Nielsen–Compustat matched database. P-values are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively. Each observation is at the year-firm level. The number of observations is 981.

| | $r_{f,t}$ | $n_{f,t}$ | $n_{f,t}$ (in module) | $n_{f,t}$ (beyond module) | $x_{f,t}$ | $x_{f,t}$ (in module) | $x_{f,t}$ (beyond module) |
|---|---|---|---|---|---|---|---|
| Correlation w/ emp. growth | 0.0255<br>(0.4095) | 0.0342<br>(0.2697) | 0.0240<br>(0.4379) | 0.0261<br>(0.3998) | 0.0099<br>(0.7490) | 0.0524*<br>(0.0904) | −0.0292<br>(0.3463) |

entrants have a comparative advantage in achieving major innovations or, as we called them within the context of the consumer goods sector, extensions (Akcigit and Kerr, 2010). And, lastly, a more innovative firm has higher levels of productivity (Lentz and Mortensen, 2008).

#### 6.4.1. Implications to labor reallocation

In the absence of direct measures of product creation and destruction, many authors have recently tried to infer the sources of growth indirectly from the patterns of job flows. For example, in the quality ladder model with R&D activities and labor decisions, the degree of creative destruction is closely related to the employment growth rates in the economy (Atkeson and Burstein, 2017; Garcia-Macia et al., 2016; Klette and Kortum, 2004; Lentz and Mortensen, 2008). Using information from our Nielsen–Compustat matched data, we test whether the relation between product reallocation and employment growth holds in the data. Our evidence is suggestive of this relation but not conclusive. We find a positive but not significant correlation between product reallocation and contemporaneous firm-level employment growth rates. Table 10 shows that for entry rates this relation is positive but insignificant, with a slightly higher correlation for incremental innovations. By contrast, the correlation is much weaker for exit rates. Exit rates of incremental innovations are positively associated with employment growth while the correlation is negative for radical innovations. Overall, the direction of these correlations shows some support for the use of indirect inference to understand the sources of innovation but many other concerns remain. For example, in the presence of adjustment costs or wage rigidities, the contemporaneous employment growth might not be the proper statistic to identify the degree of product-level reallocation activities.

#### 6.4.2. Implications to aggregate productivity

How much of the decrease in aggregate productivity can be attributed to changes in the product reallocation? Our baseline estimate in column 1 of Table 9 shows that total factor productivity increases by approximately 0.35% for every 1 percentage point increase in reallocation. Given that the reallocation rate decreased by 3.8 percentage points during the recession and that TFP declined almost 5% from 2007 to 2010 in our data, product reallocation can explain around 20 to 25% of the total decline in total factor productivity.[19] This evidence suggests that a significant drop in aggregate productivity was driven by firms slowing down their innovation activities during this period. This, in turn, decreased the dynamism in which they replaced older products with improved products decreasing the pace of quality improvements and ultimately economic growth.

#### 6.4.3. Business cycle modeling

Our work highlights the importance of studying the role of product creation and destruction in propagating business cycle fluctuations. There is a substantial amount of literature that studies how business formation affects business cycle dynamics (e.g., Chatterjee and Cooper (1993) and Jaimovich and Floetotto (2008)) and a growing body of work that emphasizes the endogenous determination of the number of products over the cycle (e.g. Bilbiie et al. (2012) and Minniti and Turino (2013)). Our results emphasize the importance of studying the role of multi-product firms in the amplification of shocks. Our estimations can be used to discipline the parameters governing the number of producers and products within each firm at different stages of the business cycle. More importantly, the fact that the reallocation rate differs substantially across different types of firms has significant implications for business cycle modeling. In traditional business cycle models, firms are homogeneous and, even in models with multi-product firms, there are no differences in the amount of products they produce or in the rate at which they introduce them to the market. We show that larger and more diversified firms launch and phase out products more often (on average) but we also provide evidence that the reallocation rate of smaller and less diversified firms is more sensitive to aggregate conditions (see Tables 1 and 3). These shifts in the distribution of sales over the cycle could potentially be an important source of amplification, and they highlight the importance of introducing firm-level heterogeneity to these models. Lastly, considerably more work needs to be done to understand the potential links between business cycles and innovation-based growth theory. Standard business cycle models do not address the determinants of product variety within firms and changes in the product scope of firms occur exogenously. Given the strong correlation we find between R&D and reallocation and the correlation between product turnover and changes in TFP,

[19] The interpretation of our results should consider the fact that they were computed using a sample of large publicly traded firms. Moreover, although within firm reallocation is by far the most important component of the overall reallocation rate, our estimates in Section 6.3 ignore the contribution of firm entry and exit.

our work shows that modeling the endogenous interaction between the innovation efforts of the firm and its product scope could substantially improve our understanding of business cycle fluctuations.

## 7. Conclusion

In this paper, we describe the extent of product innovation and reallocation in the consumer goods sector over the period from 2007 to 2013. We find a 25 percent decline in product reallocation during the Great Recession, and investigate the impact of this drop on firm-level outcomes such as revenue, product quality, and total productivity. The analysis provides several findings. First, product reallocation is strongly pro-cyclical and the cyclical pattern is overwhelmingly a consequence of within firm reallocation. Second, the rate of product reallocation is strongly related to the innovation efforts of the firms. Third, firms that have higher reallocation rates grow faster, launch higher quality goods, and experience larger gains in productivity.

Given that higher reallocation activities lead firms to grow both quantitatively and qualitatively, the fact that its pace suffered an important drop had substantial implications for aggregate growth in this period. More importantly, the fact that the reallocation rate took so long to return to its pre-recession level suggests it was an important factor in the slow recovery the economy experienced after the Great Recession. Our findings also show that industrial and innovation policies aimed at increasing economic growth should contemplate the relative importance of the product-mix decisions. This is particularly relevant for incumbent firms as they account for the majority of the decline in dynamism in the retail sector that ultimately led to important declines in total factor productivity.

## Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jmoneco.2017.11.003.

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