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Temporal Disaggregation of Business Dynamics: New Evidence for U.S. Economy*

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Abstract

We provide new disaggregated data and stylized facts on firm dynamics of the U.S economy by using a state-space method to transform Census yearly data of entry and exit from 1977 to 2013 into quarterly frequency. Entry is lagging and symmetric, while exit is leading and asymmetric along the business cycle. We select the most significant determinants of these variables by matching Census data with a new database by Federal Reserve. These determinants differ considerably among entry and exit. Finally, standard macroeconometric models estimated on our disaggregated series support the recent theoretical literature, according to which the cleansing effect of recession is mainly due to exit asymmetry.

JEL Codes: C13, C32, C40, E30, E32.

Keywords: Bayesian VAR, Dynamic Asymmetry, Entry and Exit, Firms and Establishments, Overshooting, Productivity, State-Space Models, Variable Selection.

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I INTRODUCTION

Firms are one of the pillars of any economic system. Their dynamics is an important indicator of the status of the economic activity. Having a clear view of the entry and exit of firms from the market is fundamental in order to understand the business cycle phase and address a properly calibrated policy. Despite the relevance of this issue, however, there is a lack of long-span quarterly dataset on firms dynamics, even for the U.S. economy. In fact, the dataset currently published by Census Bureau is yearly and constitutes the only long-span data source on the argument. On the other side, the quarterly time series published by the Bureau of Labor Statistics (BLS, henceforth), start in the second quarter of 1993, while data provided by ECONOMICMAGIC are monthly data from 1959 to 1996. Hence, the only time series suitable of immediate application in macroeconomic models faces with limited – and limiting – frequency. Moreover, the starting date of BLS series does not allow a comprehensive long-span analysis as required by modern macroeconomic science. This scarcity of macroeconomic data at high frequency motivates this paper, which contribution is threefold: first, we provide new disaggregated series of firm entry and exit for the U.S., which are supposed to complement the yearly Census data¹ using a state space form (SSF, henceforth)-based model introduced by [Proietti \(2006\)](#); second, we investigate the business cycle properties of the disaggregated series; third, we conduct a structural VAR analysis to understand how these variables react to a productivity shock. With respect to the latter analysis our aim is to test whether the implied responses of entry and exit at business cycle frequencies are able to confirm some recent theoretical result found by the literature on firm dynamics, and namely: (i) the procyclicality of firm entry; (ii) the countercyclicality and the overshooting of firms exit.

For what concerns the first contribution, for the first time in the literature, we disaggregate the yearly data currently in use² using the FRED-MD, a new, large macroeconomic

¹The yearly BLS data on entry and exit are aggregate time series series of all private sectors of the U.S. economy.

²All the series - the disaggregate ones and any equivalent proxies available in quarterly frequency - are here generically labelled as ‘ENTRY’ and ‘EXIT’, while, in the rest of the paper, such labels will

database describing all sectors of the U.S. economy published by Federal Reserve Bank of St. Louis and extensively described in [McCracken and Ng \(2016\)](#).³ Also, to the best of our knowledge, this is the first paper that identifies the determinants of the dynamics of the new disaggregated time series among the large number of possible variables in the same FRED-MD. To this aim, we adopt four different statistical models to understand the specific features (like serial correlation, the degree of the noise rather than smoothness) characterizing each of them. In turns, for each of these four models we select the best of three different specifications to understand the role of trends and other deterministic terms. This requires a demanding empirical exercise of variable selection among 1,608 potential candidates. We anticipate that ENTRY and EXIT are driven by mutually different sectors of the economy. Namely, while in the case of ENTRY it is not clear what sector is preponderant, in the case of EXIT the housing sector is an important determinant.

For what concerns the second and the third contribution, we carry out a descriptive analysis on the business cycle properties of our disaggregated series, jointly with a structural Vector AutoRegression (SVAR, henceforth) analysis to test their dynamic performances in response to a positive productivity shock. In particular, we extract the trend and cycle components via the standard first difference operator, the [Hodrick and Prescott \(1997\)](#) (HP) and [Baxter and King \(1999\)](#) (BK) filters⁴ and, subsequently, we classify them as leading or lagging indicators of the business cycle by looking at

be substituted to correctly identify each single series used.

³The FRED-MD is at monthly frequency and, at the time of the settlement of our investigation, it was the only available online. Since in our application the focus is in quarterly data, we aggregated the original data available from the release 2015-04. At the present date, the quarterly version of the dataset, FRED-QD, is ready for the use. All the monthly releases and the quarterly version can be downloaded at the [Michael McCracken's web-site](#).

⁴The HP and BK filters has been choosen for ease of literature comparison and should not be looked as optimal. In particular, we remark that both of the filters are characterized by a symmetric weighting scheme (that is, negative deviations from the mean are looked similarly to positive deviations. Despite our analysis reveals that many of the time series we are discussing are non-linear and dynamically asymmetric, we ignore the ‘true’ amount of asymmetry that is due to either trend component either the cyclical component. Hence, a more elaborate filtering technique is still prone to provide an output not corresponding to the same DGP. Moreover, we are aware of the [Hamilton \(2018\)](#) critique to HP, and namely the fact that it easy introduce a more complex dynamics in the time series than necessary, which is largely confirmed by our empirical investigation. Nevertheless, the previously mentioned nonlinear dynamics of our data seems to mitigate the distorting effects of the HP regression

the maximum absolute value of cross-correlations between the cyclical components of ENTRY and EXIT and the one of real GDP (RGDP, henceforth). According to our results, while ENTRY is lagging and procyclical, EXIT is a leading and countercyclical indicator. In this respect, this paper complements the empirical investigation by [Tian \(2018\)](#), with respect to whom we deepen the economic analysis on the establishment-level data. In particular, we confirm the first three empirical facts pointed by this Author with different data⁵.

Then, we use our new quarterly data to test if the cleansing effect of the recessions exposed and modelled by [Caballero and Hammour \(1994\)](#), according to which EXIT (ENTRY) is (a)symmetric around the mean is a reasonable hypothesis⁶. According to the econometric framework originally introduced by [Sichel \(1993\)](#), such an hypothesis implies, respectively, that the time series of EXIT are negatively skewed either in levels (*deepness*) either in first differences, while ENTRY is only in its first-differences (*steepness*). We call *dynamic asymmetry* the case of joint steepness-and-deepness. To this aim, we assume that the same time series follows a generalized smooth transition autoregression (GSTAR) introduced by [Zanetti Chini \(2018\)](#) because it allows the dynamically asymmetric cycles by construction. Thus, we test for the null hypothesis that our disaggregated data present the same rate of acceleration in the cycle either in recession either in expansion (corresponding to steepness without deepness). This hypothesis is rejected in many cases of EXIT and often not rejected in ENTRY, hence supporting the above mentioned theory.

Finally, the results of the structural SVAR analysis in response to productivity shock are in line with the recent literature, so that entry is procyclical while exit is coun-

⁵“**Fact 1.** Overall, firm birth rate is pro-cyclical and firm death is counter-cyclical. **Fact 2.** Firm death shows ambiguous cyclicalities and its (counter-)cyclicalities are sensitive to whether the chosen cyclical indicator is a level measure or a growth rate. [...] **Fact 3.** Cyclicalities in firm birth or death varies significantly across sectors. For the majority of the nine sectors, firm birth is more pro-cyclical than firm death is countercyclical and the counter-cyclicalities in firm death is sensitive to whether the business cycle measure is a level or a growth rate. Across sectors, within-sector firm births comove, and so do within-sector firm deaths.” [Tian \(2018\)](#), pp. 301–304, the bold is by Author.)

⁶“Noting that business cycles are highly asymmetric, with recessions shorter but much sharper than expansions, our model would predict that those asymmetries would be smoothed out in the creation process. The evidence confirms this prediction: creation is roughly symmetric around its mean, while destruction is highly asymmetric” [Caballero and Hammour \(1994\)](#), pp. 1351–1352).

tercyclical and overshoots its long-run value for several periods before reverting to its steady state value. Thus, we conclude that our new quarterly time series mimic pretty well the two main features found by the economic literature on firm dynamics, and namely: i) the pronounced dynamic asymmetry of firm exit and the symmetry of firm entry described in [Caballero and Hammour \(1994\)](#); ii) the overshooting effect of exit described in [Rossi \(2019\)](#) and also found in [Hamano and Zanetti \(2017\)](#)⁷.

From a theoretical perspective, the literature related to our paper is the one on DSGE models with firm dynamics and its effects on business cycle. At the current state, the theoretical contributions on this topic are mainly focused on firms' entry.⁸ Fewer papers ([Cavallari, 2015](#); [Hamano and Zanetti, 2017](#); [Clementi and Palazzo, 2016](#); [Asturias et al., 2017](#)) model firms exit in such a peculiar framework. For what concerns the literature of temporal disaggregation, since the seminal contribution by [Friedman \(1962\)](#), this literature has considerably evolved in several directions: [Denton \(1971\)](#) considers the disaggregation problem via constrained maximization; [Chow and Lin \(1971\)](#), [Fernandez \(1981\)](#) and [Litterman \(1983\)](#) via static regression models⁹; finally, an alternative methodology introduced by [Ghysels et al. \(2007\)](#) substitutes the Kalman Filter estimation used in the SSF method via modified regression based on a mixing function (see also [Quilis \(2018\)](#) for a survey). Despite the last approach is more intuitive to deal with large dataset, in this paper we adopt the SSF method to better understand the dynamics of the firm entry and exit associated to many exogenous indicators singularly considered, as we will see in a moment.

The paper is so organized: after a comprehensive discussion of data in Section II, we describe the statistical methodology in Section III, whereas Section III.I introduces briefly the SSF and the models here adopted; Section III.II explains the variable selection ex-

⁷[Rossi \(2019\)](#) stands-out for her New-Keynesian model with endogenous entry, exit and banking sector. [Hamano and Zanetti \(2017\)](#) also provide a model with endogenous exit. However, they consider a model with flexible prices and perfect financial market.

⁸See [Bergin and Corsetti \(2008\)](#); [Jaimovich and Floetotto \(2008\)](#); [Etro and Colciago \(2010\)](#); [Bilbiie et al. \(2012\)](#); [Lewis and Poilly \(2012\)](#); [Siemer \(2014\)](#); [Bergin et al. \(2014\)](#); [La Croce and Rossi \(2018\)](#). These papers consider an exogenous and constant exit probability of firms from the market. Hence, they are not able to disentangle the role of firms exit with respect to firms' entry.

⁹The SSF method capable to encompass many of the previously mentioned models estimated by Augmented Kalman Filter (AKF).

ercise and its relationship to the disaggregation; Section [III.III](#) introduces the GSTAR model and the dynamic (a)symmetry test. The illustration of our empirical findings is done in Section [IV](#): namely, Section [IV.I](#) discusses about the testing and filtering exercises, while the disaggregation’s diagnostics-and-selection exercise and the structural VAR analysis are analyzed in Sections [IV.II](#) and [IV.III](#), respectively. Finally, Section [V](#) discusses the relevance (and the limits) of our results and concludes. A separate Supplement gives additional results and details on statistical method here adopted.

II DATA

The Business Dynamics Statistics (BDS), published by Census Bureau Research Data Centers, is only official long-span dataset on firm dynamics for U.S economy. It gives information about 24 variables on the dynamics of the production sector. The total number of firms, establishments and workers, the number of establishments opened and closed, the number of job creations and destructions (measured either at job and employees) and the number of startups and firm shutdowns are just a sample of the variety of these data; Table [1](#) reports details of this peculiar and the other dataset here adopted or mentioned. These data are available in different levels of measurement (that is, at firm, establishment and employee level) and in several levels of aggregation – that is for either the entire U.S. economy, as well as for each State, and also for each of the nine sectors in which the economy has been divided. In this paper, when referring to this peculiar dataset, we will consider only the series corresponding to the entry and exit of establishments, defined as “the single physical locations where business is conducted or where services or industrial operations are performed” (*cit.* by [Census website’s definitions](#)). This is motivated by the fact that there is no an explicit measure of entry and exit of whole firms, so that these proxies are assumed to represent better such a dynamics, despite at a lower level of aggregation. However, the most of the firms considered by this dataset are single-establishment. This implies that establishment entry/exit are good proxies of firm entry/exit. All the data are available in yearly

frequency from 1977 up to 2015 (current release)¹⁰. These can be also analyzed for age and size of firms/establishments. In our analysis, we will consider only macro-aggregated data for the U.S. economy without any further restriction. In turn, BDS data summarize the confidential data of Longitudinal Business Databases, a census of business establishments and firms covering all industries in all U.S.

Analysts interested in higher frequency samples can rely on two other sources:

- (i) BUSINESS EMPLOYMENT DYNAMICS from Bureau of Labor Statistics (BED or, alternatively, BLS, henceforth). This source provides a quarterly census of the labor force in private establishments from 1992:Q3 and measures the net change in employment at the establishment level. According to the BLS definition, a net increase (decrease) in employment comes from opening (closing) establishments. Openings are either establishments with positive third month employment for the first time in the current quarter, with no links to the prior quarter, or with positive third month employment in the current quarter following zero employment in the previous quarter; closings are either establishments with positive third month employment in the previous quarter, with no positive employment reported in the current quarter, or with positive third month employment in the previous quarter followed by zero employment in the current quarter. In what follows, we label these series as ‘OPENINGS’ and ‘CLOSINGS’.

Alternatively, it is also possible to use the two series of establishment birth and death for total private sector (‘BIRTHS’ and ‘DEATH’ - or ‘B’ and ‘D’ - respectively, henceforth) available from the same source with starting date in 1993:Q2. These series are direct observations of the number of firms/establishments. According to the source, the 95% of the firms in this dataset are single-establishment. Hence the series here considered are supposed to be a better proxy of firm dynamics. [Osotimehin and Pappadà \(2016\)](#) use BED data to justify their theoretical model on business cycle and firm dynamics with financial frictions without any

¹⁰When this paper was initialized, we adopted the 2015 release the time span of the data was up to 2013. We maintain this release to avoid problems of variation in the estimates that often characterizes official datasets, as in our case.

empirical investigation on their time-series properties.

- (ii) **ECONOMAGIC**. It provides a monthly series on the number of new business incorporations from 1959:M1 to 1996:M9.

Despite their similar nature, these two sources measure different objects. Incorporations concern firm level of aggregation, while, on the other hand, establishments are often partitions of the firm. Consequently, the observations have different order of magnitude: if one aggregates the Economagic’ s monthly series, the resulting values are, approximately, a half of the observed BLS ones. A practical implication of this remark is that no interpolation is possible between the BLS and ‘Economagic’ series, so that the above mentioned macroeconomic literature is forced to stay to the evidence of short samples, or to make theoretical assumptions on the low of motion of firms’ entry without any empirical counterfactual. Perhaps more astonishing, the ‘Economagic’ data are the basis of a recent strand of literature (see [Bergin and Corsetti \(2008\)](#); [Lewis and Poilly \(2012\)](#); [Bergin et al. \(2014\)](#); [Lewis \(2013\)](#) among others), despite the exact definition of incorporation therein used is not available.

Thus, firm dynamics is not observed and commonly measured by a proxy – the employment level – quite imperfect. This is evident from a look at the correlation of these series with RGDP (see the Table 1 of Supplement). Our new longer-span time series on firm dynamics overcomes this measurement error problem.

As the next Section explains, the disaggregation of a low-frequency time series is strictly related to the choice of an high-frequency series to use as benchmark. What time series should be adopted? In principle, any possible macroeconomic time series generically related to the estimation of GDP aggregate. To this aim we make use of FRED-MD, a new, publicly accessible dataset constituted by 134 series divided in eight sectors incorporating also revisions and data changes. This peculiar choice is motivated by the [McCracken and Ng \(2016\)](#) finding that predictive power of their common factors is capable to mimic the chronology of the business cycle as well as previous econometric literature. As the next Section explains in detail, the yearly ENTRY/EXIT series

are regressed on all these variables in quarterly frequency by in order to obtain a new quarterly series of the regressand.

III METHODS

III.I Temporal Disaggregation

In a temporal disaggregation exercise, measurements of some variable are available only over s consecutive periods, where $s = 4$ if moving from yearly to quarterly, 12 from yearly to monthly and so on. In our case, the annual total of a macroeconomic (flow) variable (i.e. ENTRY/EXIT) has to be redistributed across the quarters using related series that are available at higher frequency (or ‘indicators’).

More in details, the problem of temporal disaggregation can be solved via *interpolation* or via *distribution*. The former consists in estimating of the missing values of a *stock* variable at points in time that have been systematically skipped by the observation process. The latter arises when *flow* variables are in the form of linear aggregates, as for the case of observations available only as totals or as averages over s consecutive periods. In our exercise, the low-frequency variable to be disaggregated are Establishment Entry/Exit from BED. These are flow variables, not trading day-adjusted, so that the distribution approach is here adopted. The high frequency indicator variable is one of the FRED-MD variables. We will consider all of them, but a peculiar attention is given to the Industrial Production Index (IP, henceforth) at quarterly frequency, seasonally adjusted¹¹.

We consider four of these models: (i) the Chow-Lin (CL-SSF); (ii) two augmented distributed lag models and, namely, the ADL(1,1)-SSF and the (iii) the ADL(1,0)-SSF; (iv) the Litterman-SSF model. The estimation of each of these models is described in the Supplement. In the last part of this Section, we propose to apply them to every 134 FRED-MD indicators, select the most significant among them via an empirical rule

¹¹This choice is due to the fact that this series coincides with the series denoted “INDPRO” (identification number: 6), and, according to the [online appendix](#) to [McCracken and Ng \(2016\)](#), is comparable with the FRED Global Indices series M116460980.

and averaging the selected ones. We label this approach ‘Combination’ Method.

Let y_t denote a realization of a (univariate) time series observed at $t = 1, \dots, T$ having the role of dependent variable; x_t a realization of an exogenous regressor and corresponding to the indicator; ϵ_t a realization of a disturbance vector. Furthermore, let multiple time series be denoted in bold and matrices in capital and the initial realization of the same object be denoted with a lower-case “1”; finally a $'$ denotes a transposition, $\doteq$ equal by definition and $\equiv$ and equivalence. Then we rely on the following state space representation for the general model for temporal disaggregation:

$$\left\{ \begin{array}{ll} y_t = z'_t \alpha_t + x'_t \beta, & t = 1, \dots, T \\ \alpha_t = \alpha_{t-1} + W'_t \beta + H \epsilon_t, & t = 1, \dots, T \\ \alpha_1 = a_1 + W_1 \beta + H_1 \epsilon_1, \quad \epsilon_t \sim N(0, \sigma^2), \quad \beta \sim N(0, \sigma^2 V), \end{array} \right\} \quad (1)$$

where: α_t is a vector of state elements, β_t a parameter vector and V is the variance matrix of β . The first equation is named *measurement equation*, while the second one is the *transition equation*. The vectors and the matrices W_t contain exogenous regressors, that enter respectively the measurement and the transition equations and zero elements corresponding to effects that are absent from one or the other equations. The initial state vector, α_1 , is expressed as a function of fixed and known effects (a_1), random stationary effects ($H_1 \epsilon_1$, where the notation stresses that H_1 might differ from H), and regression effects, $W_1 \beta$.

We assume that β is diffuse. This holds if the process has started in the indefinite past. This assumption has been done just for convenience and can easy be weakened¹².

III.II Variable selection and combination of many disaggregates

The SSF-based disaggregation previously described holds for a single time series. This means that, in terms of system (1), we are assuming x_t is $[T \times 1]$ vector. This is hard to justify in many applications because, in principle, the resulting disaggregated time

¹²In particular, β_t could be assumed to vary over time, see [Durbin and Koopman \(2012\)](#) for more complex specification of the latent component model. Anyway, we find that our data do not makes such a complex dynamics more useful than the simpler one here adopted.

series y_t could be sensitive to the choice of the single indicator.

We circumvent this problem by considering N indicators, represented by $\mathbf{X}_t = [\mathbf{x}_1, \dots, \mathbf{x}_N]$ a $[T \times N]$ matrix containing all the MD-FRED variables; the SSF disaggregation machinery is thus repeated for all the N elements of X_t . In this way, one can use informations from all the sectors of the economy. Consequently, we produce N differently disaggregated processes collected in $[T \times N]$ matrix $\hat{\mathbf{Y}}_t = [\hat{\mathbf{y}}_1, \dots, \hat{\mathbf{y}}_n, \dots, \hat{\mathbf{y}}_N]$, with y_n representing the $[T \times 1]$ vector of the process disaggregated via system (1) (which in turn corresponds to the n -th indicator of X_t) and " $\hat{\cdot}$ " denoting the fact that the series is the result of an estimation of y_t .

Then, the combination of all disaggregated processes contained in $\hat{Y}_t$ is a simple average:

$$\hat{y}_t^C \doteq \frac{1}{N} \sum_{n=1}^N y_{t,n}^s, \quad (2)$$

with $y_{t,n}^s$ denoting the time series at time t disaggregated according to the univariate SSF using the n -th indicator. The equation (2) conveys the series labeled *AVEntry* and *AVExit* – to underline the fact that they are an average of many single processes. What of these $y_{t,n}^s$ should be chosen? This is a classical variable selection problem. Recently, the econometric literature is adopting complex machine-learning procedures like boosting or LASSO-type estimators; see, *inter alia*, [Bai and Ng \(2009\)](#); [Caner and Kock \(2018\)](#). Since this paper aims to produce new, reliable data, we prefer to rely on a more empirical approach based on the four-steps rule here summarized:

- Selection Rule 1.*
1. Estimate all the (competing) models and check the t -value associated to their parameters; if some of them is low, consider the model as weak and potentially discardable.
 2. Compute a standard information criterion (namely, the Akaike and the Schwarz's criteria – AIC and BIC, henceforth) corresponding to the estimated model; the candidate with lower value is preferred; in case that these criteria indicates a model different to Step 1, the preference is given to the information criteria indication; if still these two criteria do not coincides, preference is given to BIC.

3. Use diagnostic test to check the hypothesis of normality and no remaining serial correlation; if both of them are rejected, discard the model.
4. If still too many candidates pass the steps (1) – (3), check the form of the Likelihood function: if multimodal or flat, discard the model. Moreover, check the correlation between final disaggregation estimates and the cyclical component of IP: if this is below a critical threshold, discard the model.

Despite the huge amount of human work and time consumption, this rule allows us to capture some economic insights that algorithmic approaches may mis-consider.

III.III Testing for dynamic asymmetry

The process $\{y_t^{s,j}\}_1^T$ corresponding to the time series going from $1, \dots, t, \dots, T$ obtained by disaggregating (yearly) y_t at the higher frequency s by using the (generic) indicator j , follows a GSTAR(p) model if

$$y_t^{s,j} = \phi' \mathbf{z}_t + \theta' \mathbf{z}_t G(\boldsymbol{\xi}) + \epsilon_t, \quad \epsilon_t \sim I.I.D.(0, \sigma^2), \quad (3)$$

$$G(\boldsymbol{\xi}) = \left(1 + \exp \left\{ - \prod_{k=1}^K h(c_k, s_t) \right\} \right)^{-1}, \quad (4)$$

where $\mathbf{z}_t = (1, y_{t-1}^{s,j}, \dots, y_{t-p}^{s,j})'$, $\phi = (\phi_0, \phi_1, \dots, \phi_p)'$, $\theta = (\theta_0, \theta_1, \dots, \theta_p)'$ are autoregressive parameter vectors; $G(\boldsymbol{\xi}) \doteq G(\boldsymbol{\gamma}, h(c_k, s_t))$ is a transition function of the vector of nonlinear parameters $\boldsymbol{\xi} = [\boldsymbol{\gamma}, h(c_k, s_t)]$, which is formed by the vector $\boldsymbol{\gamma} = (\gamma_1, \gamma_2)$ and a function of the K location parameter c_k ; the transition variable $s_t = y_{t-d}^{s,j}$, with $d > 0$ denoting the delay, and defining $\eta_t \equiv (s_t - c)$ for ease of notation,

$$h(\eta_t) \doteq \begin{cases} \gamma_1^{-1} \exp(\gamma_1 |\eta_t| - 1) & \text{if } \gamma_1 > 0, \\ \eta_t & \text{if } \gamma_1 = 0, \\ -\gamma_1^{-1} \log(1 - \gamma_1 |\eta_t|) & \text{if } \gamma_1 < 0, \end{cases} \quad (5)$$

for $\eta_t \geq 0$ and

$$h(\eta_t) \doteq \begin{cases} -\gamma_2^{-1} \exp(\gamma_2 |\eta_t| - 1) & \text{if } \gamma_2 > 0, \\ \eta_t & \text{if } \gamma_2 = 0, \\ \gamma_2^{-1} \log(1 - \gamma_2 |\eta_t|) & \text{if } \gamma_2 < 0, \end{cases} \quad (6)$$

for $\eta_t < 0$. The transition function $G(\cdot, \cdot)$ is continuous in γ . Equation (5) (equation (6)) models the higher (lower) tail of the transition function, so it allows for the asymmetric behavior introduced by the slope parameter γ_1 (γ_2), which controls the velocity of the transition in each half of the same function. When $\gamma_1 = \gamma_2 = 0$, $G(\cdot)$ is a standard logistic curve; differently, $\gamma_1, \gamma_2 > 0$ ($\gamma_1, \gamma_2 < 0$), $h(\eta_t)$ is an exponential (logarithmic) rescaling that increases more quickly (more slowly) than a standard logistic function does. This parametrization ensures that the global slope remains unchanged with respect to the traditional symmetric logistic function. The requirement that $h(\cdot) = \eta_t$ when the slope parameter is zero is necessary for ease of exposition and allows us to build a test for the null of dynamic symmetry against the alternative hypothesis of dynamic asymmetry. Moreover, in our applications, we assume $K = 1$, although other distributions of exponential family can be easily achieved.

Since the degree of dynamic asymmetry depends exclusively by parameters γ_1 and γ_2 , testing for the presence of dynamic asymmetry in the process y_t requires the following hypothesis system:

$$H_0 : (\gamma_1, \gamma_2) = (0, 0) \text{ vs } H_1 : (\gamma_1, \gamma_2) \neq (0, 0). \quad (7)$$

which, in turn, leads to a simple score test measured by the following Lagrange-Multiplier statistic:

$$S(\boldsymbol{\xi})^{LM} = \frac{1}{\hat{\sigma}^2} \hat{\mathbf{u}}' \mathbf{H} (\mathbf{H}' \mathbf{H} - \mathbf{H}' \mathbf{Z} (\mathbf{Z}' \mathbf{Z})^{-1} \mathbf{Z}' \mathbf{H})^{-1} \mathbf{H}' \hat{\mathbf{u}}, \quad (8)$$

where $\hat{\mathbf{u}} = [\hat{u}_1, \dots, \hat{u}_T]'$, $\hat{u}_t = y_t - \hat{\boldsymbol{\phi}}' \mathbf{z}_t - \hat{\boldsymbol{\theta}}' \mathbf{z}_t G$, $\mathbf{Z} = (\mathbf{z}'_1, \dots, \mathbf{z}'_T)'$, $\mathbf{H} = [(\mathbf{h}_1^0)', \dots, (\mathbf{h}_T^0)']'$, with denoting the sub-gradient vector evaluated under the null $[\boldsymbol{\theta}' \mathbf{z}_t G_{\gamma_1}, \boldsymbol{\theta}' \mathbf{z}_t G_{\gamma_2}, \boldsymbol{\theta}' \mathbf{z}_t G_c]'$.

Under H_0 , statistic S_1 is asymptotically distributed as a χ_n^2 , where $n = \dim(\mathbf{h}_t^0)$; see the Supplement of [Zanetti Chini \(2018\)](#) for the mathematical derivations and estimation details.

IV RESULTS

IV.I Business Cycle Analysis

A graphical inspection of the series estimated via SSF-based method introduced in previous section is shown in Figure 1. All the specifications of ENTRY are characterized by absence of outliers and noise. Differently, and perhaps more interestingly, in EXIT such ‘smoothness’ characterizes only the Litterman’s and – in lower degree – the ADL(1,0) models. This is easy to measure in periods of recession, where the ADL(1,0) parametrization ensures a non-deep cycle in recession and (relatively) rounded peaks. Let consider the example of ENTRY during the recession phase of 1990: the series obtained via ADL(1,1)-SSF passes from 179,000 in 1990:Q4 to 170,000 in 1991:Q2, while the ADL(1,0)-SSF one ranges from 176,000 to 173,000 – that is, in phase of recession the magnitude of the difference of the level measured between the two dates changes up three time according to the model used. The other two parametrizations stay in the middle between the other ones above described. Differently, EXIT passes from 126,000 to 151,000 in ADL(1,1), while in ADL(1,0) from 134,000 to 144,000. In terms of difference, EXIT ranges from 25,000 to 10,000 – that is, more than the double in the opposite direction. Thus, a correct specification of the SSF is not a secondary nor easy issue. Instead, the dynamics of the BLS proxies is radically different from the one of our SSF-disaggregated samples (see the Supplement). Now, we need to classify all of them as leading or lagging indicators of the economic activity. To this aim, we compute the maximum absolute value cross-correlations between the cycle of disaggregated series and that of the RGDP. It seems reasonable to limit our search for the corresponding maximum absolute cross-correlation to a range between lags and leads of 6 quarters for

the ENTRY and 8 quarters for the EXIT¹³. Table 3 shows the results for all the dataset used in this paper and either univariate and combined SSF-based disaggregates (see next Section IV.II for the selection of the variables). Three important facts arise: (i) our ENTRY series is generally a lag and pro-cyclical indicator of the business cycle with maximum absolute cross-correlation at the lag 3 for the BK and the HP filter and at the lag 8 for the linear difference filter. Exit is less easy to define: although in two cases on three (using BK- and difference-filter) it is anti-cyclical, the timing is ambiguous: under BK-filter it is strongly leading, while, if using HP-filter, it is strongly lagging; still differently, under LDiff the sample becomes almost-coincident. (ii) Instead the combined measure of ENTRY is unambiguously lagging and pro-cyclical, while EXIT unambiguously leading and anti-cyclical. (iii) On a completely different side, all the BLS proxies are generally pro-cyclical. Namely, OPENINGS and BIRTHS are coincident indicators, while CLOSINGS (DEATHS) are generally lagging (leading). The pro-cyclicity of ENTRY and the ambiguous counter-cyclicity of EXIT (if relying only on IP as single indicator) here underlined constitute the first two facts by Tian (2018). However, our results have also a fundamental discrepancy with respect to the same article: the timing structure of our disaggregated series. In facts, while we find that ENTRY is lagging and EXIT is leading, the opposite holds for the Author¹⁴. Moreover, our business cycle analysis shows that the filtering technique is not a trivial choice when investigating the trend and cycles properties of the series.

Once that the basic of the business cycle features and components of the time series ENTRY and EXIT disaggregated according to the methodology explained in Section III has been extracted, we test the null hypothesis of dynamic symmetry on them in

¹³We enlarged the number of possible lags/leads whenever it was not possible to find a maximum inside this range in order to avoid spurious results. In facts, whenever the duration of the business cycles is short, a variable that leads (lags) the reference cycle by several months can be wrongly classified as lagging (leading) since it can be closer to the previous cycle than to the next; see Altissimo et al. (2010) for a discussion of this problem. In the Supplement, we show that the cycle of ENTRY is shorter than the cycle of EXIT. Thus, the choice of a different number of leads/lags for the two disaggregated series.

¹⁴**“Fact 6. Firm birth (death) positively leads (lags) the business cycles. This mismatched timing results in the observed asymmetry in the cyclicity of firm birth and death together with the sensitivity in the latter on the aggregate level, within sectors, for small firms, and death hazard by age for young firms.”** (bold is by Author), Tian (2018, p. 307)

order to investigate the effectiveness of qualitative forecasts induced by the [Caballero and Hammour](#)’s theory. For each of these variables, we consider quarterly and yearly growth rates. The HP-cyclical components are also considered for robustness check. Our investigation involves different delay corresponding to one quarter, one year and two years to allow a better understand - medium- and long-run effects of the cleansing, if any. According to the results reported in Table 2, the null hypothesis of dynamic symmetry of ENTRY is rejected in just one case on 16 in the short-run, 4 in the medium run and six in the long-run. For what concerns EXIT, the same hypothesis is rejected almost everywhere if considering quarterly growth rates (in either non-filtered and filtered time series), while in the yearly growth rates it is in only three cases. Thus, we confirm that ENTRY has a very limited asymmetric effects on the output fluctuations. Similarly, their prediction that the asymmetry of EXIT is high is also confirmed, albeit not if using data in yearly growth rates.

IV.II Variable Selection and Diagnostics for Combination Method

We deals with 134 indicators to be used for four models in three specifications per each, corresponding to the case of no deterministic kernel, a constant and constant plus trend; thus, we have total of 1,608 potential candidates to be evaluated. Before to enter in the details of this exercise, we compute the estimated correlation coefficients of the ENTRY/EXIT with each of the FRED-MD indicator. These are shown in Fig. 2: noticeably, while ENTRY is positively correlated with almost all of them, EXIT presents a large set of indicators that have not negative correlation sign – coherently with previous results in Table 3. Moreover, only a very small set of the indicators (less than 10% of the total for ENTRY, around 12% for EXIT, approximately) stays above the critical level. Interestingly, IP is significantly correlated only with EXIT (-0.45, approximately). These results confirm the [Tian \(2018\)](#)’s Fact 3 and give us an *ex-ante* idea of the number of the variable to select.

Table 4 reports the results of a the model estimation and selection for the single case of IP. Despite the fact that just one indicator variable has been adopted, several consider-

ations can be done: first, the constant component captures almost all the significance of the estimation for almost all the cases; in facts, the other parameters of the same model with constant-plus-trend (that is, the regression effects ' x' -s and the '*trend*') are characterized by very low t -values; consequently, the trend components are never significant. Second, the autocorrelation of order two is never rejected, neither in ENTRY nor EXIT. On the other side, the normality is a characterizing feature of the ENTRY, but not of EXIT. Third, the information criteria indicates the ADL-type of model (namely, ADL(1,1) for AIC, ADL(1,0) for BIC) specification with constant plus trend. However, in light of the low t -values in almost all other parameters when a deterministic trend is assumed, we choice the Litterman specification with no deterministic terms as second best for both ENTRY and EXIT. Finally, the correlations between the estimated models and IP are not helpful to select the model: while in ENTRY all the highest correlations are captured by the poor estimates of ADL(1,0), in EXIT these are distributed over three models on four.

Table 5 reports the results of the exercise, repeated for all the other 133 indicators of FRED-MD. For space issues, we show only the significant t -values of the selected parameters. There is a strong difference in the variety among ENTRY and EXIT, either in terms of models either in the type of variables selected: the former measure is characterized by a set of different parametrizations, the latter is almost completely characterized by an ADL(1,0). Among the overall set of indicators, only three of them (Production Index of ISM Manufacturing, Housing Permits and Weekly Hours in Goods-Producing) are common to both ENTRY and EXIT. A part of these three variables, ENTRY and EXIT are moved by mutually different variable in different sectors: namely, ENTRY is driven by four sectors: Outputs and Income, Labor Market, Consumptions and Orders and Prices; on a different hand, Housing constitutes a half of the most significant indicators associated to EXIT.

IV.III Structural Analysis

Once the statistical properties of the new disaggregated series have been investigated, it is possible to use them for structural econometric analysis. To this aim, we estimate small BVAR models and show the IRFs to orthogonalized shocks to labor productivity as well as to the total factor productivity (TFP, henceforth); see the Supplement for IRFs associated to TFP shocks.¹⁵ We use data on RGDP, inflation, and the three alternative proxies of firm dynamics, and namely: (i) the disaggregated series of AVEntry and AVExit obtained with the multivariate SSF method; (ii) the series of ENTRY and EXIT obtained with the univariate SSF method; (iii) the BLS quarterly series of BIRTHS and DEATHS. The bayesian approach to structural analysis has been considered for its versatility and capability to address the issue of short sample size. In fact, it avoids sampling errors in estimation of IRF bands that may occur when sample is short or, equivalently, when the model is highly over parameterized, see [Sims and Zha \(1998\)](#). We estimate five different BVAR specifications, corresponding to five different alternative Entry and Exit proxies (labeled M1–M5, henceforth). Table 6 gives more details on model definitions and description of the samples. Namely, we consider a sample size 1993:Q2-2013:Q4 for the BVAR estimated with the BLS series of BIRTHS and DEATHS, while a longer sample (1983:Q1-2013:Q4) is instead used for the BVAR estimated using the disaggregated (AV)Entry and (AV)Exit. In this way, we exclude the period of high inflation and the monetary regime change of the early-80s and consider only the Volcker-Greenspan-Bernanke period. Two BVARs using the disaggregated series for the sample 1993Q2-2013Q4 are also considered to compare their analogues which adopt BLS data. All the variables under consideration are expressed in logarithms of

¹⁵We consider labor productivity for two reasons. First, because it is the variable considered in the theoretical model by [Bilbiie et al. \(2012\)](#); [Hamano and Zanetti \(2017\)](#); [Rossi \(2019\)](#), among others. Secondly, it is available in levels and in quarterly terms from FRED database, while TFP is available only in annual terms. Nevertheless, for robust check we use the standard TFP measure computed by [Basu et al. \(2006\)](#). This series is quarterly, but available only in log-difference terms. Thus, we consider the TFP only in the BVAR estimated in log-deviations. In the Supplement, these estimations will be compared with the same BVAR where also labor productivity is in logarithm difference.

the levels. Precisely, for each variable Y we adopt LY to label its log-transform¹⁶. As it is now standard in the literature, this implicitly allows for the possible presence of cointegrating relations, without imposing restrictions on the long-run properties of the model, see [Sims et al. \(1990\)](#). The reduced form of the BVAR(p) is:

$$\mathbf{y}_t = \mathbf{A}_1 \mathbf{y}_{t-1} + \mathbf{A}_2 \mathbf{y}_{t-2} + \dots + \mathbf{A}_p \mathbf{y}_{t-p} + \mathbf{u}_t, \quad (9)$$

where $\mathbf{A}_j$, ($j = 1 \dots p$) are $(N \times N)$ coefficient matrices and $\mathbf{u}_t = [u_{LabProd,t}, u_{RGDP,t}, u_{ENTRY,t}, u_{EXIT,t}]'$ is a white noise vector of time series with $\mathbf{u}_t \sim (\mathbf{0}, \Sigma_u)$.

For each system under investigation, we estimate a BVAR(2) using Minnesota Priors of 0.8 on the autoregressive coefficient of the first lag for the distribution of parameters. These priors are justified by the short sample size. In fact, in this framework, it is assumed that the VAR residual variance-covariance matrix Σ_u is known; here we make use the entire variance-covariance matrix of the VAR system estimated by OLS¹⁷. As a robustness check, we estimate the same model specifications under Normal Diffuse Priors; a prior of 0.8 on the autoregressive coefficient of the first lag has been set also in this case; the results are reported in the Supplement. Finally, we choose a lower triangular Cholesky identification and order LLabProd as first entry of the vector of dependent variables, such that shocks on impact to productivity do affect the other variables, while shocks on impact to the other variables do not affect productivity. This ordering has been widely used in the literature, see [Bloom \(2009\)](#), among many others. In what follows, we consider responses to 1 percent shock to the labor productivity.

The IRFs resulting from the BVAR under Minnesota Priors are plotted in Figures 3 – 7. In all of the plots, the median responses to one-standard-deviation increase in

¹⁶For example, in M1 the N vector of observable time series is $\mathbf{y}_t = [LLabProd_t, LCPI_t, LRGDP_t, LAVENTRY_t, LAVEXIT_t]'$, where LLabProd is the logarithm of labor productivity, $LCPI_t$ is the logarithm of Core CPI Index, while $LRGDP_t$, the logarithm of real GDP, LAVEntry and LAVExit are the logarithms of the disaggregated series of AVEntry and AVExit (that is the ones obtained using the multivariate UC method) and the vector length is T with $T = 122$ at the full sample. All these series has been downloaded from FRED database.

¹⁷Since the model estimates all the equations simultaneously, the assumption of a diagonal matrix of the original Minnesota prior, which in turn implies independence between the VAR coefficients of different equations and justified at that time of limited computational power as it estimates the model equation by equation, is not necessary.

the innovations to labor productivity are depicted by solid lines, while dashed lines represent 84% and 16% confidence intervals. The RGDP increases in response to a productivity shock, while inflation falls down. Again, all the BVAR specifications here considered confirm that firm creation is pro-cyclical, and – perhaps more interestingly – persistent. On the opposite side, firm destruction is countercyclical and, remarkably, overshoots its long run level in the medium run. These results are robust to the use of the Normal Diffuse Priors (see the Supplement).

The SVAR models here presented are perfectly in line with the descriptive findings reported in Table 3: in fact, the prolonged leading effect (almost two-years) of the ‘averaged’ measures on EXIT is compatible with the overshooting in long-run that the same variable shows in Figures 6 – 7 whereas the negative peak of the corresponding IRF is at the 8-th period. This suggests that ENTRY and EXIT are, respectively, pro-cyclical and countercyclical if conditioned to a positive productivity shock. However, the timing of the recovery is considerably different for all the models under consideration: more immediate in EXIT (approximately 20 quarters to return to the steady-state) and less immediate for ENTRY (almost 40 periods in M4 and M5; more than 50 in M1). We underline that the other different proxies of firm destructions seem to be less inertial than firm creations and overshoot their long run level in the medium run. This means that our disaggregated, long-span time series are a more interesting alternative to the BLS ones.

V CONCLUSIONS

The recent advances in macroeconomic theory make the availability of new disaggregated time series data on firm dynamics an important issue. This need is here satisfied by applying a state-space-based temporal disaggregation method to currently available data on entry and exit of firms at establishment level. This allows economists to avoid to infer on (qualitatively very different) micro-data such as the creation and destructions of jobs adopted by recent empirical literature (see, among the others, Davis and

[Haltiwanger \(1992, 1999\)](#); [Davis et al. \(2012\)](#)). Our quarterly time series of establishment entry and exit are feasible proxies of business cycle. More specifically, they mimic pretty well the two main features found by the economic literature, and namely (i) the pronounced dynamic asymmetry of firm exit and the symmetry of firm entry described in [Caballero and Hammour \(1994\)](#) and (ii) the overshooting effect of exit described in [Rossi \(2019\)](#). This is not the case of BLS proxies that the recent theoretical literature adopt without any preliminary investigation.

Several conclusions can be done by our inquiry: first, the dynamics of temporally-disaggregated BDS variables are consistent with the economic theory of the cleansing effect of the recession. However, our econometric analysis is silent with respect to the aggregate demand, albeit the RGDP here adopted may be seen as a proxy of it. Nevertheless, the recent empirical findings by [Canepa and Zanetti Chini \(2016\)](#) and [Zanetti Chini \(2018\)](#) on dynamic asymmetry in important macroeconomic variables (housing, production and unemployment rate) make us confident in this respect. Thus, we strongly recommend the use of macroeconometric models for business cycle that allow dynamics to vary according to the cycle phase, as well as the use of models that treat entry non specularly to exit. Second, the positive reaction of the real income and the consequent inflation's negative reaction to a productivity shock support the New-Keynesian theories. These results are compatible with previous macroeconomic literature on endogenous firms dynamics (see [Lewis \(2009\)](#) among the others). Third, and more specifically, our statistical analysis of the drivers of entry and exit among the FRED-MD make us supportive of the models that link housing to business cycle and establishment exit. Finally, the finding that entry of establishments cannot be associated with one or two sectors makes this variable potentially more ambiguous than its counter-cyclical counterpart. In turn, this opens more questions than it was supposed to answer and creates a new challenge for theoretical models on firm dynamics. A deeper effort is necessary to better understand this point.

More in general, temporal disaggregation methods should account for the increase in dimension and availability of macroeconomic datasets and possible nonlinearity of the

indicator(s). This suggests that two important topics for future methodological research on this topic are the introduction and/or adaptation of variable selection algorithms recently appeared in Econometrics and the introduction of a high-dimensional, nonlinear structures to capture the dependence and correlations between the most economically meaningful variables. Finally, our study focuses exclusively on the number of establishment entry/exit and omits to investigate the other variables of BDS dataset. A replication of the same disaggregation-and-selection exercise to all the other BDS yearly time series seems us fundamental to have still better perspective on U.S. business cycle. In turn, this requires to optimize the statistical tools adopted methodology. The multivariate approach by [Guay and Mourin \(2015\)](#) seems a good starting point.

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Figure 1
The disaggregated series

Notes: This figure plots the values of the time series resulting from the four state-space models for temporal disaggregation mentioned in Section III and exposed in the Supplement. The quarterly indicator (IP) adopted for this figure is seasonally adjusted. Colored bands correspond to the NBER recessions. Software used: OxMetrics

Figure 2
The correlations between BDS data and the FRED-MD indicators.

Notes: This figure shows the correlation coefficients between the yearly Establishment Entry (Exit) and the FRED-MD indicators. In the X-axis, the indicators (aggregated from monthly to yearly frequency via averaging) are depicted by their identification number (see the [online appendix](#)); the Y-axis corresponds to the correlation coefficients. The two horizontal lines represent the Upper and Lower Critical Level of the correlation; these last has been set arbitrarily to ± 0.35 .

Figure 3
IRFs from BVAR-M1 with Minnesota Priors.

Notes: This figure shows the responses of the BVAR-M1 system to a labor productivity shock of one standard deviation. Sample: 1983Q1–2013Q4.

Figure 4
IRFs from BVAR-M2 with Minnesota Priors.

Notes: This figure shows the responses of the BVAR-M2 system to a labor productivity shock of one standard deviation. Sample: 1983Q1–2013Q4.

Figure 5
IRFs from BVAR-M3 with Minnesota Priors.

Notes: This figure shows the responses of the BVAR-M3 system to a labor productivity shock of one standard deviation. Sample: 1993Q3–2013Q4.

Figure 6
IRFs from BVAR-M4 with Minnesota Priors.

Notes: This figure shows the responses of the BVAR-M4 system to a labor productivity shock of one standard deviation. Sample: 1993Q3–2013Q4.

Figure 7
IRFs from BVAR-M5 with Minnesota Priors.

Notes: This figure shows the responses of the BVAR-M5 system to a labor productivity shock of one standard deviation. Sample: 1993Q3–2013Q4.

TABLE 1

Main features of datasets on firms' dynamics currently in use.

<i>Dataset name</i>	<i>Type of aggregate</i>	<i>Source</i>	<i>Frequency</i>	<i>Time span</i>	<i>Economic variables/sectors</i>
BDS	Flow	Census webpage	Yearly	1977 – 2013	No. of Firms/Establishment/Employees Establishments Entry/Exit Rate of Establishments Entry/Exit Job Creations/Destructions Net Job Creations/Destructions Job Creations Births/Deaths " Rate Job Creation/Destruction Continuers " Rate Reallocation (Rate) Firmdeaths
BED	Flow	BLS webpage	Quarterly	1992:Q3 – 2013:Q4 1993:Q2 – 2013:Q4	Openings and Closings Births and Deaths
ECONOMAGIC	Flow	Economagic.com	Monthly	1959:M1 – 1996:M9	Business incorporations
FRED-MD/QD	Flow	FED St. Louis	Monthly/ Quarterly	1959:M1 – 2013:M12 1959:Q1 – 2013:Q4	Output and Income Labor Market Consumption and Orders Orders and Inventories Money and Credit Interest/Exchange Rates Prices Stock Market

Notes: This table reports the main characteristics of each economic dataset mentioned in this paper. Namely, for each dataset, column (i) indicates the label; column (ii) the type of aggregate; column (iii) the (web) source; column (iv) the frequency of the observations; column (v) the time span; and column (iv) the main economic variables or the classification of the sector of activity contained in the dataset. Notice that some datasets or variables contained in the same repository might have different frequency (as in the case of FRED-MD) or different time spans (as in the case of BLS data). Different datasets have different definitions for the same label: in facts the Births/Deaths measured by BLS shouldn't be confused with "Job Creation Births/Deaths" computed by BDS. For formal definitions, see the sources. In the set of BDS (FRED) variables, the bold indicates the variable in which we are interested in (the sector where is the variable that we adopted as high frequency indicator).

TABLE 2
Dynamic asymmetry tests for U.S. data on firm dynamics.

ENTRY					
Transform	d	ADL(1,0)	ADL(1,1)	Chow-Lin	Litterman
Quarterly growth rates	1	0.0908	0.1919	0.7190	0.9520
	4	0.0026	0.4619	0.3718	0.2513
	8	0.0007	0.2088	0.1073	0.0058
Yearly growth rates	1	0.8830	0.9478	0.9060	0.9508
	4	0.3213	0.9229	0.9797	0.0187
	8	0.1585	0.8421	0.8470	0.1453
Quarterly growth rates, cyclical component	1	0.4019	0.4017	0.5428	0.9213
	4	0.2019	0.2019	0.1522	0.0003
	8	0.1737	0.0760	0.0189	0.0050
Yearly growth rates, cyclical component	1	0.8935	0.8935	0.7419	0.8163
	4	0.6964	0.6964	0.8004	0.0065
	8	0.8225	0.8225	0.8675	0.0576
EXIT					
Transform	d	ADL(1,0)	ADL(1,1)	Chow-Lin	Litterman
Quarterly growth rates	1	0.0002	0.0006	0.0010	0.0213
	4	0.0005	0.1180	0.0984	0.0901
	8	0.0748	0.0086	0.0085	0.0185
Yearly growth rates	1	0.5927	0.3418	0.3125	0.3655
	4	0.0026	0.0724	0.2648	0.3977
	8	0.0739	0.1417	0.1406	0.2939
Quarterly growth rates, cyclical component	1	0.0002	0.0005	0.0010	0.0213
	4	0.0000	0.0421	0.3484	0.5901
	8	0.2746	0.0049	0.0085	0.0885
Yearly growth rates, cyclical component	1	0.0927	0.3109	0.3125	0.3625
	4	0.0060	0.2286	0.2500	0.3740
	8	0.0739	0.1964	0.2170	0.2900

Notes: This table reports the p -values corresponding to the test statistic (8) for the null hypothesis of dynamic symmetry, for disaggregated data on firm dynamics in yearly and quarterly growth rates, for all the models mentioned in Section III.I. The delay parameter d corresponds to one, four and eight quarters. Values leading to a rejection of the null hypothesis are marked in bold.

TABLE 3
Stylized business cycle facts

<i>Data Types</i>	<i>Series</i>	<i>Lead</i>	<i>Lag</i>	<i>Sign</i>
Disaggregated (Univariate SSF)	Entry-BK		3	+
	Entry-HP		3	+
	Entry-LDiff	8		+
	Exit-BK	6		-
	Exit-HP		8	+
	Exit-LDiff		1	-
Disaggregated (Combined SSF)	AVEntry-BK		3	+
	AVEntry-HP		3	+
	AVEntry-LDiff		1	+
	AVExit-BK	6		-
	AVExit-HP	7		-
	AVExit-LDiff	7		-
BLS	Openings-BK		0	+
	Openings-HP		0	+
	Openings-LDiff		0	+
	Closings-BK		5	+
	Closings-HP		5	+
	Closings-LDiff		4	+
BLS	Births-BK		0	+
	Births-HP		0	+
	Births-LDiff		1	+
	Deaths-BK	4		-
	Deaths-HP	5		+
	Deaths-LDiff		2	+

Notes: This table reports the cross-correlation analysis of the cyclical component of different measure of ENTRY and EXIT respect to the RGDP. ‘Lead’ (‘Lag’) indicates the point where the cross-correlation function – in absolute value – of ENTRY (EXIT) and RGDP reach its maximum; a zero value of lag/lead indicate that the series is a coincident indicator of the business cycle. The sign ‘+’ (‘-’) means that the maximum cross-correlation in the indicated lead/lag is positive (negative). The cyclical components extracted by the HP filter assume penalization parameter $\lambda = 1600$ and the ones obtained by BK filter assume parameters $\lambda_0 = 1.5$, $\lambda_1 = 8$ and $K = 12$ (that is, $3 \times s$).

TABLE 4
Model selection and diagnostic for SSM-disaggregated series with IP as indicator

ENTRY											
ADL(1,1)				ADL(1,0)				Chaw-Lin			
nd		c		nd		c		nd		c	
t		t		t		t		t		t	
Log-Lik.	-446.654	-439.909	-437.692	-446.977	-438.760	-441.123	-439.866	-445.319	-445.410	-445.871	-445.871
ϕ	0.993	0.847	0.805	0.994	0.805	0.812	0.801	0.001	-0.674	0.001	0.001
σ^2	7.7e+07	8.9e+07	8.9e+07	7.9e+07	9.3e+07	9.6e+07	1.0e+08	7.9e+07	7.9e+07	7.8e+07	7.8e+07
x_1	-213.773	-364.872	-409.716.78	182.989	322.956.33	-241.034.76	-143.156.25	179.336	98.01	5.32	5.32
Reg. effects	[0.43]	[0.68]	[-0.77]	[2.83]	[1.54]	[-0.44]	[-0.26]	[8.24]	[0.08]	[0.29]	[0.29]
x_2	398.325.26	613.306.57	769.250.14	-	-	-	-	-280.235	-279.904	-322.922.26	-322.922.26
[t-stat]	[0.81]	[1.18]	[1.49]	-	-	-	-	[-0.56]	[0.56]	[-0.65]	[-0.65]
m	-	26.433.67	30.716.87	-	25.805	29.928.90	32.623.80	-	179.228	181.044.8	181.044.8
gt	-	[30.22]	[19.20]	-	[29.28]	[33.68]	[20.95]	-	[8.22]	[9.22]	[9.22]
			[41.89]				[33.73]	-		-339.73	-339.73
			[2.31]				[1.78]	-		[-0.22]	[-0.22]
AIC	895.31	881.82	877.39	895.95	879.53	884.25	881.73	893.83	893.83	893.74	893.74
BIC	898.31	884.82	880.38	895.95	879.53	887.24	884.73	896.83	896.83	896.74	896.74
Durbin	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DH	0.339	0.591	0.567	0.128	0.016	0.476	0.533	0.197	0.057	0.007	0.007
$\rho(\cdot, QIP)$	0.142	0.243				0.097			0.102		
$\rho(\cdot, cQIP)$	0.141	0.141				0.096			0.097		
$\rho(\cdot, YIP)$	0.246	0.258				0.231			0.233		
$\rho(\cdot, cYIP)$	0.226	0.226				0.209			0.209		

EXIT											
Log-Lik.	-444.11	-437.30	-437.69	-446.313	-438.767	-438.989	-431.944	-442.05	-442.010	-441.906	-441.906
ϕ	0.997	0.876	0.805	0.996	0.811	0.865	0.499	0.001	0.001	0.001	0.001
σ^2	6.5e+07	7.1e+07	8.9e+07	7.5e+07	9.4e+07	7.4e+07	1.4e+08	6.3e+07	6.3e+07	6.3e+07	6.3e+07
x_1	1,034.050	894.185.27	-409716.78	67,678	1,011.927	859,858.38	36,358.01	124.618	189.13	7.47	7.47
Reg. effects	[2.28]	[1.87]	[-0.77]	[1.34]	[2.23]	[1.34]	[0.08]	[7.12]	[0.23]	[-7.46]	[-7.46]
x_2	-985,080	-1,101,923.98	769,230.14	-	-	-	-	1,005,101	1,005,822.9	1,012,175.19	1,012,175.19
[t-stat]	[-2.18]	[-2.38]	[1.49]	-	-	-	-	[2.26]	[2.26]	[2.27]	[2.27]
m	-	19.339.33	30.716.87	-	21.414.20	29.928.90	64.365.34	-	124.288.68	123.533.77	123.533.77
gt	-	[24.87]	[19.20]	-	[25.12]	[23.56]	[30.98]	-	[7.10]	[7.01]	[7.01]
			[41.89]				[8.84]	-		734.32	734.32
			[2.31]					-		[0.34]	[0.34]
AIC	890.22	876.60	864.30	894.63	865.78	879.9	865.89	886.10	886.02	885.81	885.81
BIC	893.22	879.60	867.30	894.63	865.78	882.98	868.89	889.10	889.02	888.81	888.81
Durbin	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DH	0.002	0.000	0.001	0.000	0.005	0.005	0.035	0.000	0.001	0.000	0.000
$\rho(\cdot, QIP)$	0.139	-0.026				0.132			0.106		
$\rho(\cdot, cQIP)$	0.088	0.105				0.078			0.052		
$\rho(\cdot, YIP)$	-0.001	-0.034				-0.004			-0.007		
$\rho(\cdot, cYIP)$	0.084	0.127				0.087			0.090		

Notes: This table reports the estimates of the SSF-based disaggregation described in Section III.1 for the special case that the indicator variable is the U.S. Index of Industrial Production. For each of the parametrization discussed in the text we investigate the case of no deterministic kernel (nd), constant (c) and constant + trend (t) in the equations (7), (8) and (9) of Supplement. The t -value is in square brackets above each value. “AIC” and “AIC” are, respectively, the Akaike and Schwarz Information Criteria. “ $\rho(\cdot, QIP(YIP))$ ” is the correlation coefficient between the disaggregated series and the Industrial Production in quarterly (yearly) growth rates; similarly, “ $\rho(\cdot, cQIP(cYIP))$ ” is the correlation coefficient between the disaggregated series and the cyclical component of the Industrial Production in quarterly (yearly) growth rates; the cyclical component has been computed by using the [Baxter and King \(1999\)](#) filter; in every case the estimated value relates to the ‘best’ estimate among the ‘nd’, ‘c’ and ‘t’ specification. The significance threshold for correlation coefficient with IP is 0.200. The “Durbin” is the [Durbin \(1970\)](#) test for the null of no serial correlation of order two; “JB” is the [Doomik and Hansen \(2008\)](#) test for the null of normality. Significant values are in bold. Software used: OxMetrics 6.

TABLE 5
MD-FRED indicator selected for combining disaggregation estimates (excluding Industrial Production).

ENTRY							EXIT						
Label	Id	Description	Log-likelihood	Model	Regr. eff.	t-val	Label	Id	Description	Log-likelihood	Model	Regr. eff.	t-val
RETAILx	5	Retail and Food Services Sales	-444.34	Litterman	x_1 x_2	9.71 -1.69	NAPMPI	19	ISM Mnfact.: Prod. Index	-442.694	ADL(1,0)	x_1 x_2	15.10 2.21
NAPMPI	19	ISM Manufact.: Production Index	- 461.425	Chaw-Lin	x_1 x_2	36.61 -	CES06000000007'	46	Avg Weekly Hrs: Goods- Producing	-439.884	ADL(1,0)	x_1 x_2	29.46 -
UEMP15T26	30	Civilians Unemployed for 15-26 Weeks	-444.843	Litterman	x_1 x_2	9.62 1.63	AWHMAN	48	Avg Weekly Hours : Manufact.	-439.700	ADL(1,0)	x_1 x_2	30.43 1.01
CES06000000007'	46	Avg Weekly Hours : Goods- Prods.	-440.430	ADL(1,0)	x_1 x_2	37.76 -	HOUST	50	Housing Starts: Total New Priv. Owned	-441.558	ADL(1,0)	x_1 x_2	20.02 -1.63
NAPMEI	49	ISM Manufact.: Employment Index	-463.367	Chaw-Lin	x_1 x_2	30.29 -	HOUSTNE	51	Housing Starts, Northeast	-442.032	ADL(1,0)	x_1 x_2	16.75 -
PERMIT	55	New Priv. Housing Permits (SAAR)	-440.523	Chaw-Lin	x_1 x_2	44.06 -	HOUSTMW	52	Housing Starts, Midwest	-442.167	ADL(1,0)	x_1 x_2	17.03 -
BUSINVx	68	Total Business Inventories	440.523	Chaw-Lin	x_1 x_2	44.06 -	HOUSTS	53	Housing, Starts, South	-441.369	ADL(1,0)	x_1 x_2	20.39 -
OILPRICEx	110	Crude Oil, spliced WTI and Cushing	-445.380	Litterman	x_1 x_2	9.39 -	PERMIT	55	New Private Housing Permits (SAAR)	-441.253	ADL(1,0)	x_1 x_2	21.46 -
CUUR0000SAD	118	CPI: Durables	-442.278	Litterman	x_1 x_2	8.91 9.56	NAPMSDI	62	ISM: Supplier Deliveries Index	-453.393	Chaw-Lin	x_1 x_2	24.26 -
DSERG3M086SBEA	126	Personal Cons. Exp: Services	-443.159	Chaw-Lin	x_1 x_2	10.20 -							

Notes: This table reports the variables of MD-FRED selected according to the procedure described in Section III.I. These variable has been used in the 'Combination' approach to disaggregation described in Section III.I. For either ENTRY and EXIT, we report: (i) the label of the variable (first column); (ii) its identification number (second column); (iii) the estimated Log-likelihood function (third column); (iv) the model of the disaggregation exercise (fourth column); (v) the regression effects which has been considered (fifth column); and (vi) their estimated t -value (sixth column).

TABLE 6
BVAR Models description

<i>Model</i>	<i>Sample</i>	<i>Priors</i>	<i>Y_t</i>				
M1 M2	1983:Q1–2013:Q4	Minnesota	[LLabProd [LLabProd	INF INF	LRGDP LRGDP	LAVEntry LEntry	LAVExit LExit]'
M3 M4 M5	1993:Q2–2013:Q4	Minnessota	[LLabProd [LLabProd [LLabProd	INF INF INF	LRGDP LRGDP LRGDP	BIRTHS LAVEntry LEEntry	DEATHS]' LAVExit]' LEExit]'
M1b M2b	1983:Q1–2013:Q4	Normal Diffuse	[LLabProd [LLabProd	LCPI LCPI	LRGDP LRGDP	LAVEntry LEntry	LAVExit LEExit]'
M3b M4b M5b	1993:Q2–2013:Q4	Normal Diffuse	[LLabProd [LLabProd [LLabProd	LCPI LCPI LCPI	LRGDP LRGDP LRGDP	LBIRTHS LAVEntry LEEntry	LDEATHS]' LAVExit]' LEExit]'

Notes: This table reports a list of definitions of vector $\mathbf{y}_t$ to be modeled by the BVAR system (9) for structural analysis. Namely, M1–M5 are BVAR estimated using Minnesota Priors. The labels M1b–M5b indicate that the BVAR models considering the Normal Diffuse Priors.

SUPPLEMENT
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A Statistical tools

A.1 The Chow-Lin Regression Model

Let assume, for easy of explanation, that we are interested in univariate disaggregation, that is to disaggregate a single time series using a single indicator variable. The Chow-Lin model arises as a simple linear OLS regression of the observed $T \times 1$ -process y_t on the vector of the same dimensions of the indicator variable x_t multiplied by the $T \times sT$ disaggregation matrix D , and having 1-order autoregressive disturbances u_t , i.e.

$$\begin{aligned} D'_s y_t &= D'_s x'_t \beta + D'_s u_t, \quad u_t \sim N(0, D_s V D'_s) \\ u_t &= \phi u_{t-1} + \epsilon_t, \quad |\phi| < 1, \quad \epsilon_t \sim NID(0, \sigma^2), \end{aligned} \tag{1}$$

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where ϕ is an autoregressive parameter, V a variance matrix and D_s is a block-diagonal matrix of form

$$D_s \doteq \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & \dots & \dots & \dots & \dots & \dots & \dots & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & \dots & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & & \ddots & \ddots & \ddots & \ddots & \ddots & & \vdots \\ 0 & \dots & \dots & \dots & \dots & \dots & \dots & 0 & 1 & 1 & 1 & 1 \end{bmatrix}$$

for the case in which $s = 4$, that is from yearly to quarterly frequency.

In order to make (1) equivalent to the Chow-Lin regression, three noticeable assumptions on x_t must be done:

Assumption 1. x_t is strictly exogenous;

Assumption 2. x_t free of measurement errors;

Assumption 3. x_t is cointegrated with y_t .

Remark 1. The univariate framework here adopted does not affect the generality of these assumptions, since they hold for all N possible regressors, that is with $\mathbf{X}_t = [x_{1,t}, \dots, x_{N,t}]$ in place of x_t .

A.2 State Space Representation

The issue of temporal disaggregation arise as a modification of system (1) in the Main Document. In order to understand this, notice that (low-frequency) data are a sum of s consecutive values, available at time $t = 1, 2, \dots, [n/s]$, where $[\cdot]$ denote the integer part of the number n/s . Then the following holds:

Proposition 1. Let define the cumulator variable as:

$$y_t^c \doteq \psi_t y_{t-1}^c + \psi_{t-1}, \quad \psi_t^c \doteq \begin{cases} 0 & \text{if } t = s(\tau - 1) + 1, \text{ with } \tau = 1, \dots, [n/s] \\ 1 & \text{otherwise} \end{cases} \quad (2)$$

Then the state-space system

$$\begin{cases} y_t = z^{*'} \alpha_t^* \\ \alpha_t^* = T_t \alpha_{t-1}^* + W_t^* \beta + H_t^* \epsilon_t, \\ \alpha_1^* = a_1^* + W_1^* \beta + H_1^* \epsilon_1, \quad \epsilon_t \sim NID(0, \sigma^2), \quad \beta \sim N(b, \sigma^2 V), \end{cases} \quad (3)$$

where:

$$z^* = \begin{bmatrix} 0' \\ 1 \end{bmatrix}, \quad T_t^* = \begin{bmatrix} T & 0 \\ z'T & \psi \end{bmatrix}, \quad W_t^* = \begin{bmatrix} W_t \\ z'W_t + x_t' \end{bmatrix}, \quad H_t^* = \begin{bmatrix} H_t \\ z'H_t + x_t' \end{bmatrix}, \quad (4)$$

$$\alpha_1^* = \begin{bmatrix} a_1 \\ z'a_1 \end{bmatrix}, \quad W_1^* = \begin{bmatrix} W_1 \\ z'W_1 + x_1' \end{bmatrix}, \quad H_1^* = \begin{bmatrix} H_1 \\ z'H_1 + x_1' \end{bmatrix} \quad (5)$$

converts the disaggregation into a problem of estimation of a latent component model with missing observation. This is the system which is estimated for disaggregation of ENTRY and EXIT series.

Proof. This occurs simply replacing $y_t = z\alpha_t$ in (2), substituting the transition equation and re-writing:

$$y_t^c = \psi_t y_{t-1}^c + \psi_{t-1} + z'T\alpha_{t-1} + (z'W_t + x_t)\beta + z'H\eta_t, \quad (6)$$

and finally, substituting this expression in the state vector, with $\alpha_t^* = [\alpha_t', y_t^c]'$ $\square$

A.3 State-space Models for Temporal Disaggregation

Under proper arrangement, the classical [Chow and Lin \(1971\)](#) regression model as well as ADL(p,q) model mentioned in the Main Text and described above can be assumed as particular case of (3).

Case 1 (CL-SSF). When α_t is a scalar, $z = 1$, $T = \phi$ are $H = 1$, the system (3)

degenerates into a linear regression model with AR(1) errors:

$$y_t = z'_t \alpha_t + x'_t \beta, \quad \alpha_t = \phi \alpha_{t-1} + \epsilon_t, \quad \epsilon_t \sim NID(0, \sigma^2) \quad (7)$$

with $|\phi| < 1$ and $\alpha_1 \sim N(0, \sigma^2/(1 - \phi^2))$.

Remark 2. The CL model assumes full cointegration of non-stationary elements eventually present in x_t . In this case the deterministic component is handled via inclusion of regressors as, e.g., $x_t = [1, t, x_{3t}, \dots, x_{kt}]'$ and re-arrangement of the process as $y_t = \mu_t + \gamma t + \sum_j \beta_j x_j + \alpha_j$ with μ and γ being the first two elements of β .

Case 2 (Litterman-SSF). The [Litterman \(1983\)](#) model assumes that the disaggregated series follows a linear regression model with ARIMA(1,1,0) disturbances:

$$y_t = z'_t \alpha_t + x'_t \beta + u_t, \quad \Delta u_t = \phi \Delta u_{t-1} + \epsilon_t. \quad (8)$$

In this case, the system (??) is characterized by $\alpha_t = \begin{bmatrix} u_{t-1} \\ \Delta u_t \end{bmatrix}$, $z = \begin{bmatrix} 1 & 1 \end{bmatrix}$, $T = \begin{bmatrix} 1 & 1 \\ 0 & \phi \end{bmatrix}$ and $H = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$. [Fernandez \(1981\)](#) considers the case of $\phi = 0$. Two types of initialization are possible: in first, the investigator assumes that the errors u_t has started in $t = 0$ with $u_0 = \Delta u_t = 0$; in the second intialization, the stationary process has started in the indefinite past. In our application we adopt the first intialization scheme for easy of interpretation. Also this ARIMA(1,1,0) process can be extended to include a constant and a trend in $\Delta u_t = \phi \Delta u_{t-1} + m + gt + \epsilon_t$; the parameters m and g are incorporated in the vector β and the matrices W_1 and W_t are easily extended.

Case 3 (ADL-SSF). If $z' = 1$, $T = \phi$, $H = 1$, $W = [1, t, x'_t, x'_{t-1}]$, $\beta = [m, g, \beta'_0, \beta'_1]'$, the system (3) degenerates into an ADL(1,1) model with dependent variable:

$$y_t = \phi y_{t-1} + m + gt + x'_t \beta_0 + x'_{t-1} \beta_1 + \epsilon_t, \quad (9)$$

which initial conditions are, under stationarity assumption: $\alpha_1 = 0$, $W_1 = \frac{1}{1-\phi} [1, \frac{1-2\phi}{1-\phi}, x'_1, x'_1]$,

$H_1 = \frac{1}{\sqrt{1-\phi^2}}$. Still, changes are needed if assuming non-stationarity.

The more general ADL-SSF can nest also the CL-SSF. Indeed:

Remark 3. The ADL-SSF collapses to the CL-SSF if and only if:

$$\beta_1 = \phi\beta_0. \quad (10)$$

Thus, (9) can be rewritten as:

$$y_t = x_t' \beta_0 + \alpha_t, \quad \alpha_t = \phi \alpha_{t-1} + \epsilon_t \quad (11)$$

so that the ADL(1,1) model nests a CL model with stationary AR(1) errors. Similarly, when $\beta_1 = 0$, the model become an ADL(1,0). In order to verify this hypothesis, a simple one-degree-of-freedom Likelihood-Ratio test is necessary. The same test can be used to to choice between ADL(1,0) and Litterman specification.

A.4 Estimation

Estimation of system (3) is done by Maximum Likelihood. Depending on the presence of diffuse elements in matrix W or not, two estimators are possible:

Fixed: the ML estimators of β and σ^2 are:

$$\hat{\beta} = -S_{n+1}^{-1} s_{n+1}, \quad Var(\hat{\beta}) = S_{n+1}^{-1}, \quad \hat{\sigma}^2 = \frac{q_{n+1} - s_{n+1}' S_{n+1}^{-1} s_{n+1}}{[n/s]}, \quad (12)$$

with profile Log-Likelihood:

$$\mathcal{L}_{\mathcal{F}} = -0.5[d_{n+1} + [n/s](\ln \hat{\sigma}^2) + (\ln \hat{\sigma}^2 + \ln 2\pi + 1)]. \quad (13)$$

Diffuse: $\hat{\beta}$ and $\hat{\sigma}^2$ unmodified and $\hat{\sigma}^2 = \frac{q_{n+1} - s_{n+1}' S_{n+1}^{-1} s_{n+1}}{[n/s] - k}$ and the diffuse profile Log-Likelihood:

$$\mathcal{L}_{\mathcal{D}} := -0.5[d_{n+1} + [n/s - k](\ln \hat{\sigma}^2) + (\ln \hat{\sigma}^2 + \ln 2\pi + 1) + \ln |S_{n+1}|] \quad (14)$$

In both of them, the parameters β can be concentrated out of the likelihood function, whereas the diffuse case is accommodated by simple modification of the likelihood.

Remark 4. S , s , q are outcomes of the augmented Kalman Filter (KF). This algorithm, introduced by [de Jong \(1991\)](#), enables exact inferences in the presence of fixed and diffuse regression effects. In order to make it operational in our system represented by equation (2) in the Main Document, the usual KF equations are augmented by additional recursions which apply the same univariate KF to k series of zero values, with different regression effects in the state equation, provided by W_t . The outputs vectors and matrices of the AKF are the basis for the [de Jong \(1989\)](#) augmented Smoothing algorithm. This refers to the estimation of the state vector α_t and the disturbance vector u_t using information in the whole sample rather than just past data. Smoothing is an important feature because it is the basis for diagnostic checking for detecting and distinguishing between outliers and structural changes using auxiliary residuals.

A.5 The Augmented Kalman Filter and Smoother

Under the initial conditions mentioned above, and further defining $A_1^* = W_1^*$, $P_1^* = H_1^* H_1^{*'}$, $q_1 = 0$, $s_1 = 0$, $S_1 = 0$, the augmented Kalman filter consists of the following equations and recursions: for $t = \tau s$, $\tau = 1, \dots, [n/s]$ (that is, y_t^c available),

$$v_t = y_t^c - z^{*'} a_t^{*'}, \quad V_t' = z^{*'} A_t^*, \quad (15)$$

$$f_t = z^{*'} P_t^* z^*, \quad K_t = T_t^* P_t^* z^* / f_t, \quad (16)$$

$$\alpha_{t+1}^* = T_{t+1}^* a_t^* + K_t v_t, \quad A_{t+1}^* = W_{t+1}^* A_t^* T_{t+1}^{*'} + K_t V_t' \quad (17)$$

$$P_{t+1}^* = T_{t+1}^* P_t^* T_{t+1}^{*'} + H_t^* H_t^{*'} - K_t K_t' f_t \quad s_{t+1} = s_t V_t v_t / f_t \quad (18)$$

$$q_{t+1} = q_t + v_t^2 / f_t \quad d_{t+1} = d_t + \ln f_t \quad (19)$$

$$S_{t+1} = S_t + V_t V_t' / f_t \quad t = 1, \dots, T \quad (20)$$

$$(21)$$

and, alternatively, for $t \neq \tau s$, (that is, y_t^c is missing),

$$\alpha_{t+1}^* = T_{t+1}^* a_t^* \quad A_{t+1}^* = W_{t+1}^* A_t^* T_{t+1}^* \quad (22)$$

$$P_{t+1}^* = T_{t+1}^* P_t^* T_{t+1}^{*'} + H_t^* H_t^{*'} \quad s_{t+1} = s_t \quad (23)$$

$$q_{t+1} = q_t, \quad S_{t+1} = S_t \quad (24)$$

V_t' denotes a row vector with k elements. The quantities q_t , S_t , s_t accumulate weighted sum of squares and cross-products that will serve the estimation of β via generalized regression.

Notice that the quantities f_t , K_t (the Kalman gain) and P_t do not depend on the observations and that the first two are not computed when y_t^c is missing. Missing values imply that updating operations, related to the new information available, are skipped.

The augmented KF computes all the quantities that are necessary for the evaluation of the likelihood function. The filtered, or real time, estimates of the state vector and their estimation error matrix are computed as follows:

$$\hat{\alpha}_t|t = a_t^* - A_t^* S_t^{-1} s_t + P_t^* z^* \hat{v}_t / f_t, \quad P_{t|t}^* = P_t^* + A_t^* S_t^{-1} A_t^{*'} - P_t^* z^* z' P_t^* / f_t \quad (25)$$

The augmented smoothing algorithm proposed by [de Jong \(1989\)](#) can be appropriately adapted to hand missing values. Let define $r_T = 0$, $R_T = 0$, $N_T = 0$ and $\hat{v}_t = v_t - V_t' S_t^{-1} s_t$. Then for $t = N, \dots, 1$ and $t = \tau s$ (that is, y_t^c is available),

$$r_{t-1} = z^* v_t / f_t + (T_{t+1} + K_t z^{*'}) r_t, \quad R_{t-1} = z^* V_t' / f_t + (T_{t+1} - K_t z^{*'}) R_t \quad (26)$$

$$N_{t-1} = z^* z^{*'} / f_t + (T_{t+1} - K_t z^{*'}) N_t (T_{t+1} - K_t z^{*'})', \quad (27)$$

while, for $t \neq \tau s$ (that is, y_t^c missing),

$$r_{t-1} = T_{t+1} r_t, \quad R_{t-1} = T_{t+1} R_t, \quad N_{t-1} = T_{t+1} N_t T_{t+1}'. \quad (28)$$

The smoothed estimates are obtained as

$$\hat{\alpha}_{t|t}^* = a_t^* + A_t^* \hat{\beta} + P_t^* (r_{t-1} + R_{t-1} \hat{\beta}) \quad P_{t|t}^* = P_t^* + A_t^* S_{n+1}^{-1} A_t^{*'} - P_t^* N_{t-1} P_t^* \quad (29)$$

B Supplementary Results

This section reports additional results to the ones presented in the Main Text that we omitted for economy of space.

Table 1 reports the estimated correlations of the disaggregated series with other proxies from BLS.

Figure 1 plots the the cross-correlation function of the yearly BLS data with the lags of series of RGDP. The estimated bars are largely below the critical values of ± 0.20 , corresponding to the blue bars

Figure 2 displays the trend and cyclical components of our new series. According to the graph, all the series have the same path in both the components, and just in the trend some difference is visible between the two filters used; the cyclical components of single-indicator-based disaggregates and Combined SSFs ones are substantially coincident.

Figure 3 repeats the same graphical check on BLS data. This time, the scenario is qualitatively quite different: the BK filter conveys a cycle considerably smoother than the HP one. On the other hand, the HP-filtered OPENINGS has a wildly noisy trend and a short cycle (very similar to the one of BIRTHS), while the CLOSINGS and DEATHS have a dynamics different in terms of peaks and troughs; it is interesting to notice that BIRTHS (DEATHS) are more (almost) than the double of OPENINGS (CLOSINGS) in the 2007–2009 recession. These differences in the cycles can be better appreciated if

comparing the series from all different sources; this is done in Figure 4: our series anticipate the recession phase in ENTRY, albeit BLS data are ‘leading’ in EXIT measures.

Figure 5 shows that the cyclical component of the new series of ENTRY/EXIT in growth rates modelled via ADL(1,1) is associated with higher and abrupt peaks, whereas CL specification corresponds to more rounded cycles. This is a confirm of the numerical example of page 14 of Main Text. Moreover it seems to suggest that CL specification is more appropriated for ENTRY according to the Caballero and Hammour (1994) predictions on the dynamics of this variable.

Figure 6 compares the disaggregated process obtained by using only IP as indicator and the one obtained by using the combination approach discussed in Section III.II of Main Text. The two processes are very similar.

Figures 7 – 11 plot the same models M1 – M5 in Main Text but with random normal distribution as prior. The models have the same patterns of the ones obtained with Minnesota priors, despite the confidence interval enlarges, as expected by standard econometric literature. This is particularly evident for the disaggregated series of EXIT.

Figures 12 – 16 display the IRF resulting from same exercise if assuming that LabProd, ENTRY and EXIT (in their different proxies), are in log-differences; as a consequence, in this sub-groups of models, the variable of inflation is replaced by CPI. The use of data in log-deviations corresponding to M1b – M5b has effects on the magnitude of the impact but not in the general path of the whole responses. In some cases, like M2b (where EXIT seems to increase to a positive shock of the labor productivity) and in M4b and M5b (whereas the effects on EXIT is not clear due to large parameter uncertainty), the response is different.

Figures 17 – 21 plot, respectively, the models M1 – M5, where the labor productivity is replaced by an alternative measure, the Total Factor Productivity (TFP) according to the definition and data by Basu *et al.* (2006). Still, a BVAR(1) with Minnesota priors with 0.8 on the autoregressive coefficient of the first lag a lower triangular Cholesky identification, ordering the TFP as first vector entry – such that, on impact, shocks to the productivity index affect the other variables, while shocks to the other variables do not affect the productivity index – are assumed. Overall, the results confirm the Figures 1 – 5 in Main Text.

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C Supplementary Figures and Tables

Table 1
Correlations between disaggregated series and BLS data

<i>Method</i>	<i>Corr(ENTRY, OPENINGS)</i>	<i>Corr(EXIT, CLOSINGS)</i>	<i>Sample</i>
Chaw-Lin	0.2669	0.7171	1992:Q3–2013:Q4
ADL(1,1)	0.2703	0.7225	
ADL(1,0)	0.2759	0.7140	
Litterman	0.3951	0.6925	
<i>Method</i>	<i>Corr(ENTRY, BIRTHS)</i>	<i>Corr(EXIT, DEATHS)</i>	<i>Sample</i>
Chaw-Lin	0.1913	0.7322	1993:Q2–2013:Q4
ADL(1,1)	0.2260	0.7152	
ADL(1,0)	0.2502	0.6882	
Litterman	0.3550	0.6760	

Notes: This table reports the correlation between the series resulting from SSF-based disaggregation corresponding to equation (3) with several specifications and the existing quarterly (seasonally adjusted) data downloaded from BLS.

Figure 1
Cross-correlation function of BLS data with RGDP

Notes: This figure plots the cross-correlation function of the BLS data (OPENINGS and CLOSINGS) with RGDP; both the data are in growth rates. Red values indicates leads while blue value indicates lags. The two horizontal lines are the critical values for the significance of the function. The source of RGDP is the FRED –Federal Reserve Bank of St. Louis.

Figure 2
Business cycle analysis of disaggregated series

Notes: This figure shows the business cycle analysis of the RGDP (upper panel) and the ENTRY and EXIT series (central and lower panel, respectively) resulting from the application of SSF disaggregation discussed in Section III of Main Text. Namely, left (right) panels plot the trend (cycle) component extracted from the series in logarithms. The cyclical components extracted by the HP filter assume penalization parameter $\lambda = 1600$ and the ones obtained by BK filter assume parameters $\lambda_0 = 1.5$, $\lambda_1 = 8$ and $K = 12$ (that is, $3 \times s$). Colored bands correspond to the NBER recessions. The series of RGDP as well as quarterly IP adopted as indicator for disaggregation are seasonally adjusted. Software used: OxMetrics.

Figure 3
Business cycle analysis of BLS quarterly series

(a) ENTRY

(b) EXIT

Notes: This figure shows the business cycle analysis of the BLS existing quarterly series of ENTRY – in panel (a) – and EXIT – in panel (b). Left (right) panels plot the trend (cycle) component extracted from the series in logarithms. Upper (lower) panels refer to HP (BK) filter. The cyclical components extracted by the HP filter assume penalization parameter $\lambda = 1600$ and the ones obtained by BK filter assume parameters $\lambda_0 = 1.5$, $\lambda_1 = 8$ and $K = 12$ (that is, $3 \times s$). Colored bands correspond to the NBER recessions. All the series are seasonally adjusted. Software used: OxMetrics.

Figure 4
The cycle component: comparison between different proxies.

(a) ENTRY

(b) EXIT

Notes: This figure shows the cycle of BLS proxies of ENTRY – in panel (a) – and EXIT – in panel (b) for different filters. Namely, the upper (lower) panels refer to the HP (BK) filter. On the other side, left (right) panels compares these proxies with combination (univariate) measures of ENTRY/EXIT. The cyclical components extracted by the HP filter assume penalization parameter $\lambda = 1600$ and the ones obtained by BK filter assume parameters $\lambda_0 = 1.5$, $\lambda_1 = 8$ and $K = 12$ (that is, $3 \times s$). Colored bands correspond to the NBER recessions. Software used: OxMetrics.

Figure 5
Comparison of different regression models of univariate SSF disaggregation

(a) ENTRY

(b) EXIT

Notes: This figure plots the components of the univariate SSF-based disaggregation discussed in Section III of Main Document, and namely: (i) the original yearly-frequency series (upper left panel); (ii) the indicator variable (upper-right); (iii) the resulting disaggregated series according to ADL-SSF and CL-SSF models (lower-left); and (iv) the same disaggregated series, but in growth rates (lower-right). Colored bands correspond to the NBER recessions. Software used: OxMetrics

Figure 6
Comparison of univariate and combined SSF.

Notes: This figure compares the series resulting from the application of univariate SSF-based disaggregation discussed in Section III of Main Document, and combined SSF-based disaggregation discussed in the last paragraph of the same Section. Upper panels refers to ENTRY and lower panels to EXIT; on the other side, left panels plot series in levels and right panels plot the same series in growth rates. Colored bands correspond to the NBER recessions. Software used: OxMetrics.

Figure 7
IRFs from BVAR-M1 with Normal Diffuse Priors.

Notes: This figure shows the responses of the BVAR-M1 system to a labor productivity shock of one standard deviation. Sample: 1993Q3–2013Q4.

Figure 8
IRFs from BVAR-M2 with Normal Diffuse Priors.

Notes: This figure shows the responses of the BVAR-M2 system to a labor productivity shock of one standard deviation. Sample: 1983Q1–2013Q4

Figure 9
IRFs from BVAR-M3 with Normal Diffuse Priors.

Notes: This figure shows the responses of the BVAR-M3 system to a labor productivity shock of one standard deviation. Sample: 1993Q3–2013Q4

Figure 10
IRFs from BVAR-M4 with Normal Diffuse Priors.

Notes: This figure shows the responses of the BVAR-M4 system to a labor productivity shock of one standard deviation. Sample: 1993Q3–2013Q4.

Figure 11
IRFs from BVAR-M5 with Normal Diffuse Priors.

Notes: This figure shows the responses of the BVAR-M5 system to a labor productivity shock of one standard deviation. Sample: 1993Q3:2013Q4

Figure 12
IRFs from BVAR-M1b with Minnesota Priors.

Notes: This figure shows the IRFs in response to 1 standard deviation shock of labor productivity for the M1 with series in log-deviations. Sample: 1983Q1–2013Q4.

Figure 13
IRFs from BVAR-M2b with Minnesota Priors

Notes: This figure shows the IRFs in response to 1 standard deviation shock of labor productivity for the M2 with series in log-deviations. Sample: 1983Q1–2013Q4.

Figure 14
IRFs from BVAR-M3b with Minnesota Priors

Notes: This figure shows the IRFs in response to 1 standard deviation shock of labor productivity for the M3 with series in log-deviations. Sample: 1993Q3–2013Q4.

Figure 15
IRFs from BVAR-M4b with Minnesota Priors

Notes: This figure shows the IRFs in response to 1 standard deviation shock of labor productivity for the M4 with series in log-deviations. Sample: 1993Q3–2013Q4.

Figure 16
IRFs from BVAR-M5b with Minnesota Priors

Notes: This figure shows the IRFs in response to 1 standard deviation shock of labor productivity for the M5 with series in log-deviations. Sample: 1993Q3–2013Q4.

Figure 17
IRFs from BVAR-M1b with TFP Shock - Minnesota Priors.

Notes: This figure shows the IRFs in response to a shock on TFP of one standard deviation for the M1 model. Sample: 1983Q1–2013Q4.

Figure 18
IRFs from BVAR-M2b with TFP Shock - Minnesota Priors.

Notes: This figure shows the IRFs in response to a shock on TFP of one standard deviation for the M2 model. Sample: 1983Q1–2013Q4.

Figure 19
IRFs from BVAR-M3b with TFP Shock - Minnesota Priors.

Notes: This figure shows the IRFs in response to a shock on TFP of one standard deviation for the M3 model. Sample: 1993Q3–2013Q4.

Figure 20
IRFs from BVAR-M4b with TFP Shock - Minnesota Priors.

Notes: This figure shows the IRFs in response to a shock on TFP of one standard deviation for the M4 model. Sample: 1993Q3–2013Q4.

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