Employment Dynamics with Convex Hiring Rules*

Dinara Alpysbayeva and Stijn Vanormelingen†

January 31, 2020

Very Preliminary version: please do not cite or circulate

1 Introduction

With a wide availability of firm-level data, a lot of attention has been paid to the role of microeconomic adjustment behaviour in the dynamics of the aggregate economy. Trends in the volatility of economic activities attracted considerable attention. A key stylized fact established is a countercyclical movement of cross-sectional volatility and negative skewness (Bloom et al., 2018; Kehrig, 2015; Higson et al., 2004; Ferraro, 2018). By design, those studies were focusing on a firm's reaction to exogenous shocks that contribute to negative skewness or countercyclical volatility. Nevertheless, a growing body of literature on investment dynamics found the investment dispersion to positively correlate with the business cycles (Bachmann and Bayer, 2014; Bachmann et al., 2013). However, these studies are mostly silent about the drivers of the consequences of aggregate shocks.

Cyclicality in aggregate outcomes is the result of significant non-linearities in the propagation of shocks. However, a long tradition in macroeconomics studying the business cycles considers linear models, which by construction exclude non-linear dynamics. Hence, workhorse macroeconomic models cannot fully generate patterns found in the data (Auerbach et al., 2019). Ilut et al. (2018) in turn highlight an endogenous mechanism that shapes the distribution of employment growth generating countercyclical dispersion and negative skewness. They use the US microdata to

*Working Title

†ECON-CEDON, Campus Brussels, KU Leuven and VIVES, KU Leuven

document its applicability. Concave hiring rules lies at the core of the mechanism. Basically, when a firm faces a firm-level shock, they respond more to bad shocks, than to good shocks. Even though, the authors stress that the presence of the concave rule alone is able to generate certain cyclical patterns, they do not take a stand on why the hiring rule is concave in the US. One possible explanation could be that firing costs are lower than hiring costs. As a result, when a negative shock hits, the cheaper form of adjustment is to fire people.

The US labor market is characterized by a high degree of mobility facing far less rigid institutional environment, distinguishing it from other advanced countries, such as continental Europe, including Belgium. The Belgian economy is perceived to be less flexible and less dynamic. It has a strong employment protection mechanism. This constraints firms to react to market fluctuations, i.e. when the negative shock hits, firms cannot easily adjust by firing employees due to high firing costs. High adjustment costs slow firm's reactions to changes and reduces investment and employment variability (Haltiwanger et al. (2014)).

The Belgian institutional setting is more typical of European institutions, more rigid labor market compared to the US. Therefore, it could be of considerable interest to study the Belgian case because it can shed light on the reasons behind different hiring rules. More precisely, differences in the optimal response to different shocks might arise from different institutional settings. A number of studies on Europe have documented that firing costs are higher than hiring costs (Goux et al., 2001; Abowd and Kramarz, 2003; Kramarz and Michaud, 2010; Dhyne et al., 2010). Therefore, we hypothesize that hiring decisions follow a convex hiring rule in Belgium, generating pro-cyclical employment growth volatility and positive skewness. The paper tests the hypothesis.

The paper starts by documenting new facts. We begin by showing that contrary to the stylized fact of countercyclicality of most of the economic activities, the volatility of employment growth of Belgium is procyclical in cross-section and time-series. Further, we show that the distribution of employment growth is positive both in cross-section and time-series. Second, we study the distribution of the productivity innovation. We show that distribution of TFP shocks is negatively skewed and has a longer tails compared to the distribution of the employment growth. We argue that given this differences, the asymmetric hiring and firing behavior cannot be attributed to the asymmetric TFP shocks alone. Finally, using non-parametric regression we show that the hiring rule in Belgium is convex. In the near future, will complement and extend these results by looking for example at different types of workers. In Belgium, hiring and firing costs differed until 2013 between blue and white collar workers. Afterwards, firing costs were brought to the same level for both types. We can use this policy change as a natural experiment to check to what extent the shape of the hiring rule is due to firing costs.

The paper provides additional evidence on the importance of responsiveness in shaping the distribution of economic activities (Berger and Vavra, 2019; Ilut et al., 2018; Decker et al., 2018). It contributes to the debate on relative importance of exogenous shocks and endogenous responsiveness to the same shocks. Moreover, it highlights the fact that policies may shape how micro-level shocks propagate to aggregate fluctuations and are magnified. This is of central interest to industrial economics and policy-makers, in general, interested in growth and performance of firms, because it might help in designing of policies to reduce the effects of the business cycles.

TO BE COMPLETED

2 Methodology

We build our analysis on the mechanism described by Ilut et al. (2018). While Ilut et al. (2018) focus on how a concave hiring rule amplifies negative shocks, their mechanism works conversily with convex hiring rules. Given the labor and product market regulations in Belgium, we will state the mechanism using the convex hiring rule. Assume an economy with continuum of firms that make certain hiring decisions. An individual firm has an information about its future profitability, which is summarized by a sufficient statistic s. Although s can include information from multiple sources, we refer to it as the firm's "signal". Assume that the signal can be decomposed into common and idiosyncratic components, a and ε, respectively:

$$s = a + \varepsilon, \tag{1}$$

where ε is i.i.d. with mean zero and distribution function G_ε. The equation above represents both individual firm's signal and the cross-sectional distribution of signals.

Firms respond to signals by adjusting their employment. Assume that firms follow certain decision rule

$$n = f(s), \tag{2}$$

where n is employment growth rate and function f is smooth, strictly increasing and strictly convex. The function defines an optimal employment given beliefs that are formed after the realization of the signal s.

The assumption on convexity allows for asymmetric adjustments, i.e. firms respond more to positive shocks and less to negative signals. We do not take a stand on what particularly makes the adjustment asymmetric. As discussed in Ilut et al. (2018), it can be due to asymmetric hiring costs, i.e. hiring costs are lower than firing costs.

The mechanism does not require certain relationship between the shock and profitability, π. In fact, there could be a true profitability which has aggregate and idiosyncratic components by itself, and firms might respond to their private shocks on their own profitability. In this case, a would contain the aggregate component of the profitability and noise in common shocks that are correlated across firms and ε will contain the idiosyncratic component of π and noise in idiosyncratic signals that are not correlated across firms.

The relative share of the two components are not central to the argument. The only requirement is that firms respond in a convex manner to signals. The model is consistent with the traditional assumption in the productivity literature that firm-level profitability follows Markov process, i.e. firms predict their future productivity given their knowledge on current productivity, with or without additional knowledge on noise in signals.

Let $G_n(n|a)$ and $G_s(s|a)$ represent conditional cumulative distributions of employment growth and signals given common shocks to firms, a, respectively. Define high values of a as "good times", i.e. times when a firm receives on average good news about its profitability. The above made assumptions imply that the conditional variance of a signal is independent of a. Better news are reflected only in a higher mean of the signal. This is helpful in endogenizing the link between micro and macro volatility that are driven by asymmetric adjustment.

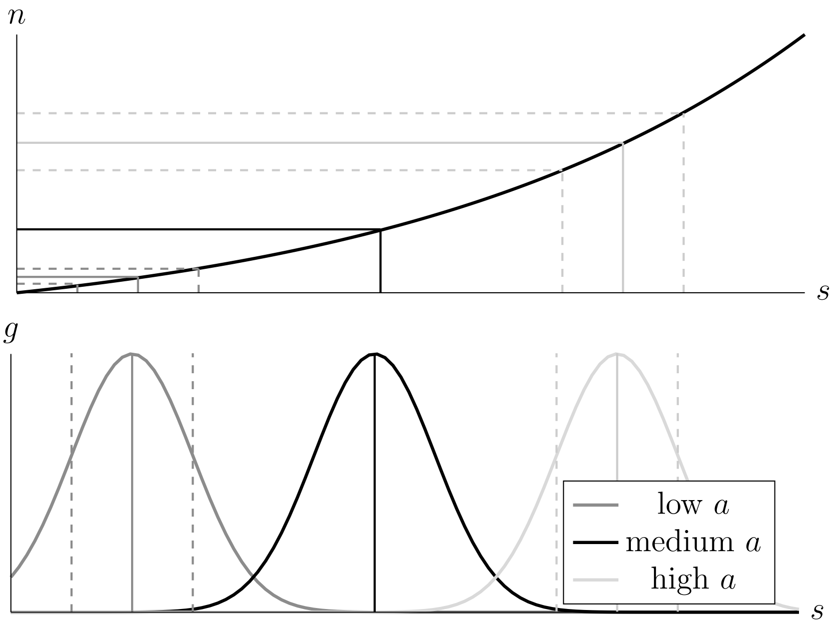
Micro and Macro Volatility of Employment

Figure 1 illustrates the intuition behind the pro-cyclical volatility. The top panel illustrates the convex response function f, with the signal realization, s, on the x-axis and employment growth on the y-axis. The bottom panel depicts three densities of signal realizations, $g_s(s|a)$, differentiated by a shift in the average signal. The middle density is a reference point. Movement to the left of the density marks an arrival of bad times, while movement to the right implies an arrival of better times. The figure clearly illustrates how asymmetric adjustment translated into pro-cyclical micro and macro volatility. Consider macro volatility first. The solid horizontal lines in the top panel correspond to mean employment growth of three signal realizations. The difference between the reference mean employment growth and the average employment growth from the low realization of a is smaller than the difference of the reference point and employment growth of high realization of signal. This implies that bad news generate less aggregate response compared to the aggregate response from good news. For the illustration of the micro volatility, consider the interquartile ranges of signals illustrated by the dashed lines. For illustrational purposes, we used the interquartile range as one measure of the cross-sectional volatility. Nevertheless, the logic equally applies to other measures. From the graph, the convex response function in fact attenuates dispersion in signals in bad times and accenuates it in good times. Formally, for any two aggregate shock realizations, where $a < a'$:

- The sensitivity of the aggregate action with respect to the shock is lower at a;
- The cross-sectional variance is lower at a;
- The interquartile range for any two quantiles is lower at a.

We direct the interested reader to the original paper of Ilut et al. (2018) for the proof.

Figure 1: Employment growth and signals



Micro and Macro Skewness of Employment

Figure 1 also suggests that asymmetric adjustments induce skewness in the cross-section and the time-series. In particular, it implies that the distribution of the employment growth should be more skewed than the distribution of the underlying shock. Define skewness using two standard measures: the Fischer-Pearson coefficient of skewness and the Kelley skewness. The Fisher-Pearson skewness is based on the second and the third moments:

$$\gamma(x) = \frac{E[(x - E[x])^3]}{var(x)^{3/2}}. \tag{3}$$

The Kellew skewness on the other hand is based on the distribution's percentiles:

$$\kappa(x) = \frac{x^{p90} + x^{p10} - 2x^{p50}}{x^{p90} - x^{p10}}, \tag{4}$$

where x^{pN} denotes the Nth percentile of the distribution of the random variable x. Formally, (proposition 2 in the original paper) for micro skewness: for any aggregate shock the coefficient of skewness of the cross-sectional distribution of employment growth, $\gamma(n|a)$, is higher than the coefficient of skewness of cross-sectional distribution of underlying shocks, $\gamma(s|a)$.[1] For macro skewness: The coefficint of skewness

[1]The same holds for the Kelley skewness, i.e. $\kappa(n|a) > \kappa(s|a)$

of the distribution of aggregate employment growth, $\gamma(E[n|a])$, is larger than the coefficient of skewness of the aggregate signal, $\gamma(a)$.[2]

It is important to note that the proposition on skewness is silent about the cyclical movements in skewness. Intuitively, changes in skewness come from changes in the curvature of the relevant range of signals, while changes in volatility are derived from changes in the slope of the response function. Hence, it is possible to have either pro-cyclical or counter-cyclical skewness, while having a pro-cyclical volatility. This implies that during the bad times the distribution can be less dispersed and at the same time be more or less positively skewed. In sum, the mechanism does not predict certain cyclical movements for the skewness of the employment growth.

Employment growth and Profitability

The basic mechanism of asymmetric adjustments is in place whenever there is a change in the mean of the distribution of firm-specific shocks during the business cycle. Under some assumptions and observations of shocks firms react, we can draw a relationship between those shocks and the employment growth distribution.

Unfortunately, the firm-specific shocks are not directly observable. In determining those shocks, we follow a large literature that focus on identification of shocks to firm profitability. We assume that de-trended profitability, denoted by Z_t^i, follow an AR(1) process:

$$Z_t^i = \rho Z_{t-1}^i + z_t^i = \rho Z_{t-1}^i + u_t^a + u_t^i, \tag{5}$$

where the innovation, z_t^i, has an aggregate, (u_t^a), and an idiosyncratic, (u_t^i), components with mean zero.

When hiring decision is made, a firm observes its past profitability, z_{t-1}^i, and a signal s_t^i, on its current innovation. The simplest assumption would be that firms observe innovation perfectly from the signal, i.e. $s_t^i = z_t^i$. Nevertheless, the mechanism still works if there is some noise in the signals. Apart from observing past profitability and current innovation level, a firm's decision will also depend on other firm or industry characteristics, or other features of the production function. At this stage, those characteristics are captured by the function f.

Since we do not observe the information set of the firm, we allow for noisy signals

[2] The same relationship for the Kelley skewness, i.e. $\kappa(E[n|a]) > \kappa(a)$.

and represent the signal for a general case:

$$s_t^i = u_t^a + u_t^i + v_t^a + v_t^i, \tag{6}$$

where given the aggregate component the idiosyncratic components are independent. If to group the components to match the notations in the equation 1, the aggregate news corresponds to the sum of the common shock, u_t^a, and the correlated noise, v_t^a, while the idiosyncratic component, ε, is the sum of the idiosyncratic part of innovation, u_t^i, and the idiosyncratic noise, v_t^i.

Suppose econometrician has information on calendar time, the role of industry and firm-specific characteristics. Then, they can recover the conditional expectation given the true innovation, z_t^i, through running a non-parametric regression of employment growth on the innovation:

$$g(z_t^i) = g(u_t^a + u_t^i) = E[f(s_t)|u_t^a + u_t^i]. \tag{7}$$

Both components of true innovation are fixed because they are "observed" by the econometrician. The correlated noise is also fixed because it is common to all firms. The only random variable that is not fixed is the idiosyncratic noise, v_t^i.

What does the unobserved noise component tell us about the underlying function of f? It is obvious that without any noise, the estimated g function is the same as the response function f. But suppose there is an idiosyncratic noise independent from the aggregate innovation component, u_t^a. From the proof of proposition 1,[3] the conditional distribution g is convex (concave, linear) if the response function is convex (concave, linear). This implies that if we find the convex regression line for the g function, then we know that the desired response function f is convex. A convex regression line signals the asymmetric adjustment underlying the mechanism.

The properties of g are still informative even if the idiosyncratic noise is not independent from the aggregate innovation component. In that case the curviture of g will reflect additionally the interaction of asymmetric adjustment and the variance. We conclude that a convex average response implies non-linear and convex decision rule under general conditions.

[3]see Appendix of Ilut et al. (2018)

3 Data

Our primary data source is the annual accounts of Belgian firms from the National Bank of Belgium. All firms with limited liabilities are required to submit the annual accounts. While a small firm can file a short form, large firms are obliged to file a complete form of the annual accounts.[4]

A book year starts on the 1st of January and end on the 31st of December. Ideally, the data should correspond to 12 months of operation. When it is not the case, we introduced a set of corrections to properly annualize the account information.

We obtained an unbalanced panel for the period 1996-2017 and selected key variables for calculating the employment growth and production function estimates, such as average number of employees (in full-time equivalents (hereinafter, FTE)), turnover (in thousand euros), value-added (in thousand euros), tangible fixed assets (proxy for capital) (in thousand euros), material costs (in thousand euros), and remuneration (in thousand euros) per firm, including NACE Rev.2 five-digit codes for each firm. We exclude all non-private sectors (NACE Rev.2 two-digit $\geq$ 84) of the economy from the analysis.

For the baseline case, we use a standard measure of employment growth:

$$n_t^i \equiv \Delta log(L_t^i),$$

which is useful because it is free of any metrics. However, it does not perform well for firms that enter or exit the sample. We ignore all firms that have gap years in their reporting or does not report its employment for more than half of its life-time. We then extrapolate missing employment data. To be internally consistent, since we need to calculate productivity innovation, we drop all observations with missing value added, tangible fixed assets and remuneration. Finally, we ignore the Belgian Railway company, because it changes its legal entity throughout the period. Since it is the largest Belgian company, its entry and exit impacts the employment growth rate distribution.

Figure A.1 shows how these changes affected the aggregate employment across

[4] A firm is considered as a large firm if it exceeds two out of three following thresholds: (i) employment of 50 FTE; (ii) turnover of 9 mln euro, and (iii) total assets of 4.5 mln euro. A firm is a small firm if it has not exceeded more than one of the above thresholds.

the sample period. We can see that the aggregate employment after the necessary cleaning and from the original data follow the same evolution.

We do not introduce any trimming or winsorization to the data, usually done in the literature to get rid of the outliers, because we believe the tails of the firm level distributions are important to better understand the aggregate movements.

The analysis is based on average 107,396 firms per year for 1996-2017 year period. The pooled dataset comprises 219,186 unique firms. The sample on average covers at least 71% of non-public sector employment in Belgium ($\approx$ 1.7 mln FTE out of $\approx$ 2.4 mln) in any given year. Table 1 presents summary statistics of key variables. An average Belgian firm active in private sector employs on average 16 employees, generates around 1,308 thousand euro in value-added and pays around 49 thousand euro average wage per year.

Table 1: Summary statistics

	Obs.	**Mean**	**SD**	**Min**	**Max**
turnover (1000 euros)	792754	15081.829	205957	0	32971880
value-added (1000 euros)	2347071	1308.296	18341	0	4551431
employment (FTE)	2347071	15.767	187	0.5	47729
tangible fixed assets (1000 euros)	2347071	1140.084	21557	0	3680862
material costs (1000 euros)	796841	12534.484	195536	0.2	32108478
wage bill (1000 euros)	2347071	778.825	9249	0	1640402
blue-collar workers (FTE)	2247006	8.118	92	0	60366
white-collar workers (FTE)	2247006	7.961	157	0	70037
hours effective (1000)	2137833	26.411	312	0.005	86466

4 Results

Employment Growth Distribution in Cross-Section and Time-Series

Figure 2 displays the year-by-year evolution of the standard deviation and the interquartile range (IQR) of the cross-sectional distribution of employment growth. Both of them show that firms differ in their employment changes: on average, the firm at the top quartile growth employment by 4 percent more than the firm at the bottom quartile. The standard deviation across all firms is 33 percent. Figure 2 shows that the dispersion of employment growth declines during recessions and increases during the booms, i.e. pro-cyclical movement of the cross-sectional volatility. As Table 2 presents, both dispersion measures are higher during the booms.[5]

Moreover, we observe a declining trend of both measures of dispersion across the sampling period. This is consistent with Bijnens and Konings (2018) that report a decline in business dynamism for Belgium for a longer time-span.

Table 2: Cross-sectional moments of employment growth

	Moments			
	$SD_t(n_t^i)$	$IQR_t(n_t^i)$	$\gamma_t(n_t^i)$	$\kappa_t(n_t^i)$
Long-run average	.326	.042	.024	.128
Booms	.328	.049	.136	.140
Recessions	.323	.045	-.024	.123
Great Recession, 2008-2009	.322	.031	-.077	.103
Corr($dE_t^{aggr}, Moment_t$)	.475**	.645**	.508**	.479**
Avg. No. obs./year	97398			

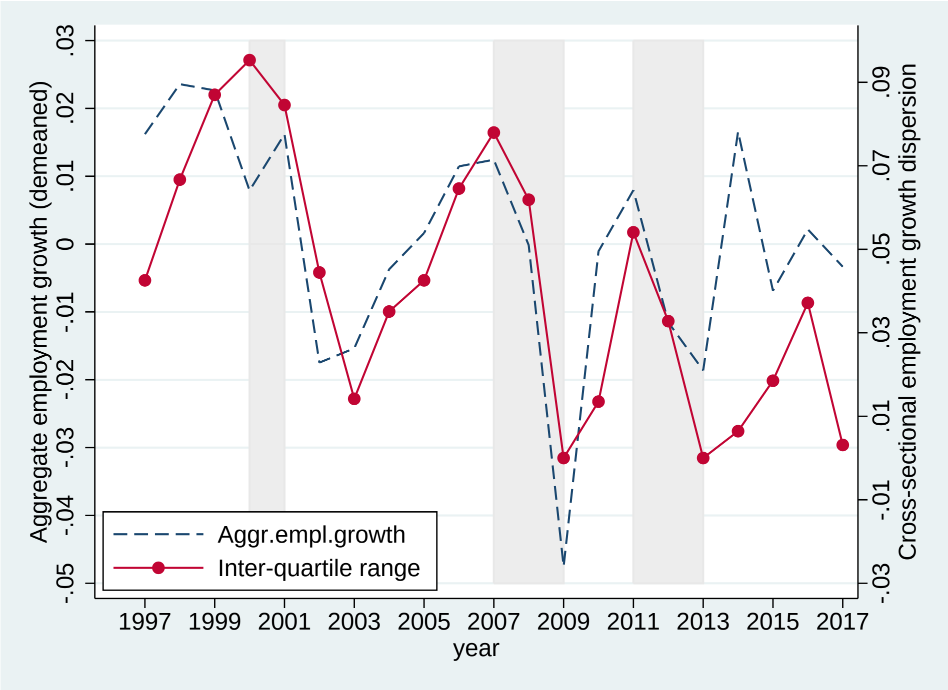
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

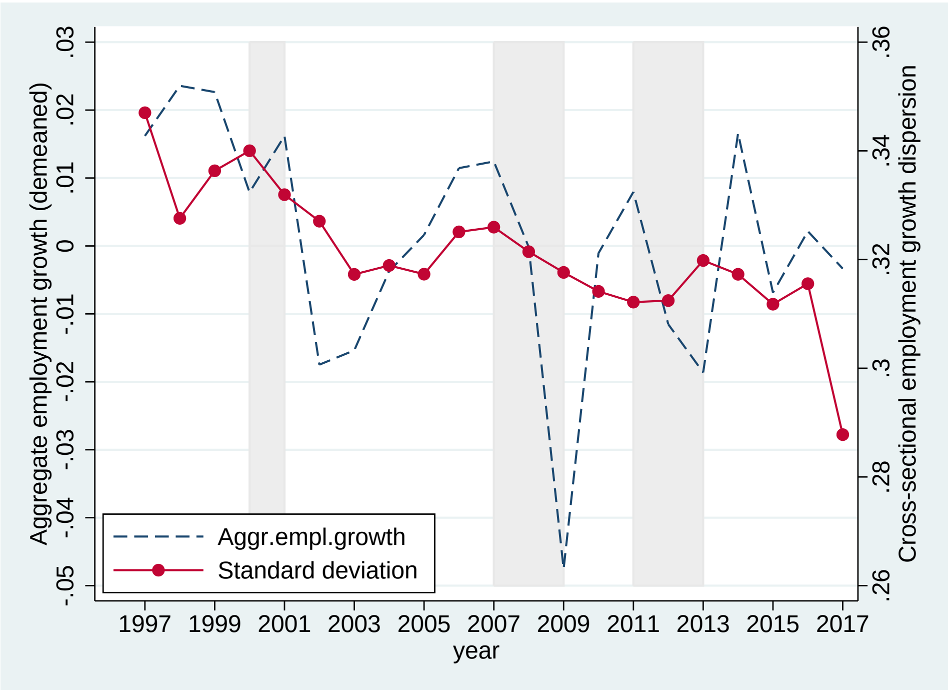
Note: These are the averages of the moments of the cross-sectional employment distribution plotted in Figures 2-3. dE_t^{aggr} denotes the growth rate of aggregate employment. Recessions are defined as years with two consecutive negative quarterly GDP growth rates. Booms are defined as years with GDP growth above its trend. To identify boom and recession years we use quarterly GDP growth data from OECD.

Figure 3 displays year-by-year evolution of the coefficient of skewness and Kelley skewness calculated using equations 3 and 4, respectively. As Table 2 shows, both measures are positive on average. This means that, on average, firms that contract shrink by less than firms that expand. The long-run average of the coefficient of skewness is 0.024, and that of the Kelley skewness is 0.128. Both of the measures

[5] Recession years: 2001, 2008-2009, 2012; Boom years: 1997, 1999-2000, 2004, 2006-2007, 2010, 2014, 2015-2017.

Figure 2: Dispersion of the cross-sectional distribution of employment growth

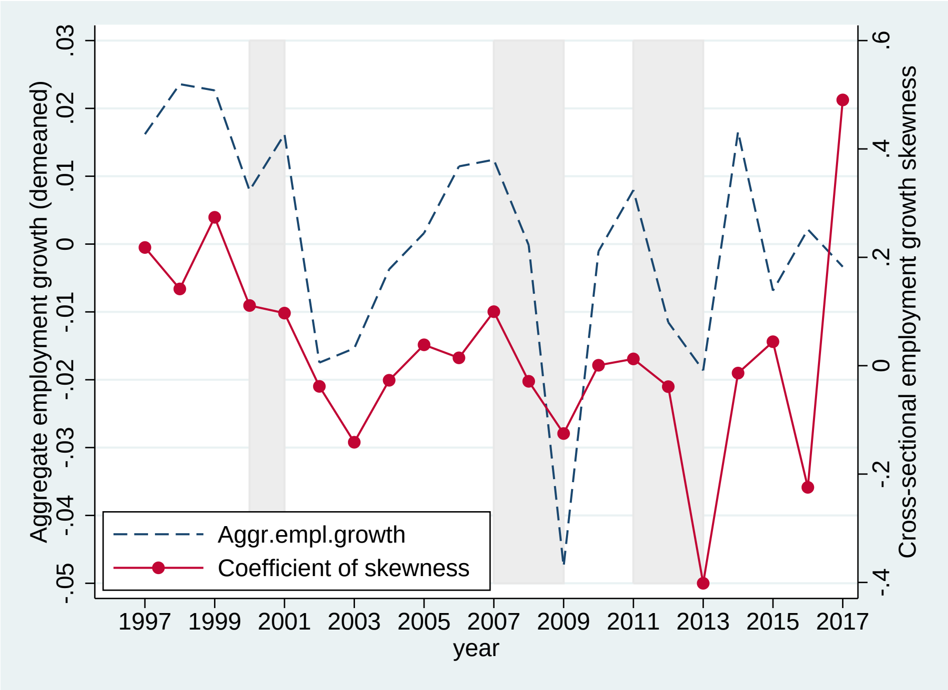


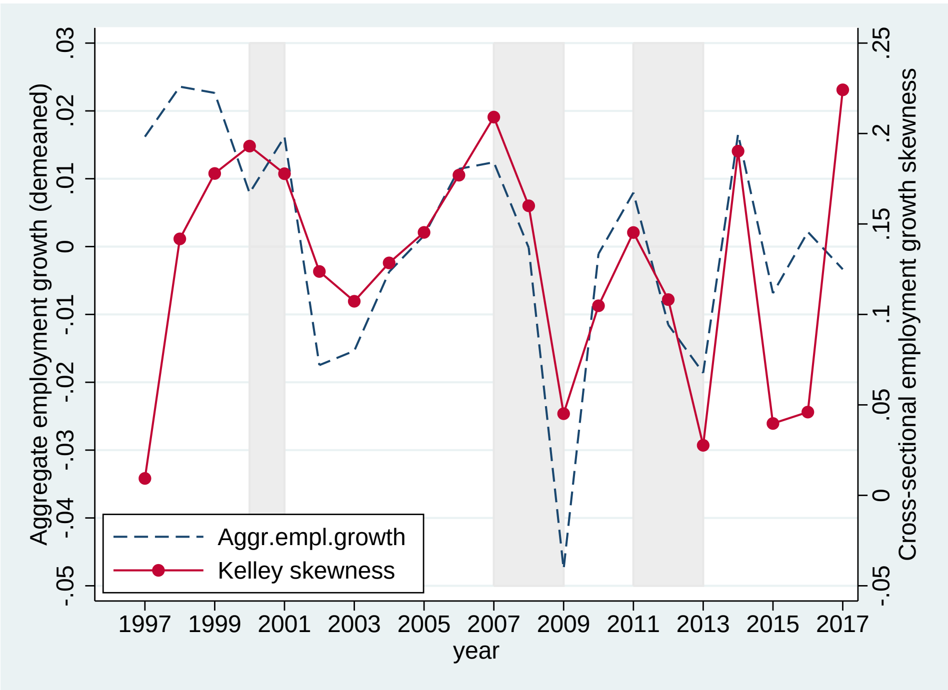


Note: On the right axis, this figure displays the year-by-year standard deviation (top) and interquartile range (bottom) of employment growth across firms. On the left axis, the gray dashed line represents demeaned aggregate employment growth. OECD recessions are marked by the vertical gray bars.

do appear to be strongly pro-cyclical. The correlation coefficient with aggregate employment is statistically significant at 5% level.

Figure 3: Skewness of the cross-sectional distribution of employment growth





Note: On the right axis, this figure displays the year-by-year skewness measures, $\gamma(n_t^i)$ (top) and $\kappa(n_t^i)$ (bottom) of employment growth across firms. On the left axis, the gray dashed line represents demeaned aggregate employment growth. OECD recessions are marked by the vertical gray bars.

TO BE COMPLETED

The model predicts positive skewness and pro-cyclical volatility of employment growth not only in the cross-section, but also in the time-series, both at the firm-level and at higher levels of aggregation. Here, we compute time-series moments for individual firms, NACE Rev.2 three-digit industries, NACE Rev.2 one-digit industries and the aggregate economy. The time-series standard deviation, Vol_t, and the time-series skewness, $Asym_t$, of employment growth are constructed within 3-year rolling windows:

$$Vol_t^i \equiv \sqrt{\frac{1}{4}\sum_{\tau=-1}^{1}(n_{t+\tau}^i - \bar{n_t^i})^2}, \tag{8}$$

$$Asym_t^i \equiv \frac{\frac{1}{4}\sum_{\tau=-1}^{1}(n_{t+\tau}^i - \bar{n_t^i})^3}{(Vol_t^i)^3} \tag{9}$$

where $\bar{n_t^i} \equiv \frac{1}{3}\sum_{\tau=-1}^{1} n_{t+\tau}^i$ is the average employment growth of firm i in the 3-year window around t. We limit our attention to 3-year rolling windows because a longer window would filter out too many changes and the sample period is too short. Moreover, we consider only those firms that at least operate 3 consecutive years. We also construct this time-series measures on different levels of aggregation, to examine if the micro-level patterns wash-out at higher levels of aggregation. We also account for a trend, because we do not want any long-run trends to affect the business cycle results.

Figures 4 and 5 display the time-series standard deviation and skewness, respectively, of the average across firms and the aggregate economy.[6] In Table 3 we report the long-run and cyclical properties of time-series dynamics at all four aggregation levels. As predicted by the mechanism, the time-series volatility of employment growth decreases during recessions for the firm level. However the relation is not very strong (correlation coefficient between the volatility and the employment growth is significant at 10% significance level). At higher levels of aggregation, the pattern found in the cross-section disappears. There is no obvious cyclical pattern at higher levels. We observe positive time-series skewness at all aggregation levels. Time-series skewness exhibit strong pro-cyclical behaviour, but the relation weakens

[6]Graphs for Vol_t and $Asym_t$ at the NACE Rev.2 three-digit and one-digit levels are added at the end of the document. The patterns look similar.

by each aggregation (firm level correlation coefficient is 0.7, while it is 0.4 at the aggregate level). At all levels of aggregation correlation between time-series skewness and employment growth is statistically significant.

Table 3: Time-series moments of employment growth

	Aggregation Level			
	Firm	**NACE 3-digit**	**NACE 1-digit**	**Aggregate**
		A. Volatility		
Long-run average	.127	.034	.022	.009
Booms	.128	.034	.021	.008
Recessions	.126	.033	.024	.013
Great Recession, 2008-2009	.123	.032	.029	.017
Corr($dE_t^{aggr}, Moment_t$)	.346*	.157	-.347	-.407
		B. Asymmetry		
Long-run average	.000	.013	.079	.041
Booms	.023	.130	.336	.304
Recessions	-.027	-.109	-.379	-.830
Great Recession, 2008-2009	-.049	-.233	-.442	-1.359
Corr($dE_t^{aggr}, Moment_t$)	.713***	.625***	.540**	.384*
Avg. No. obs./year	109,293	157	16	1

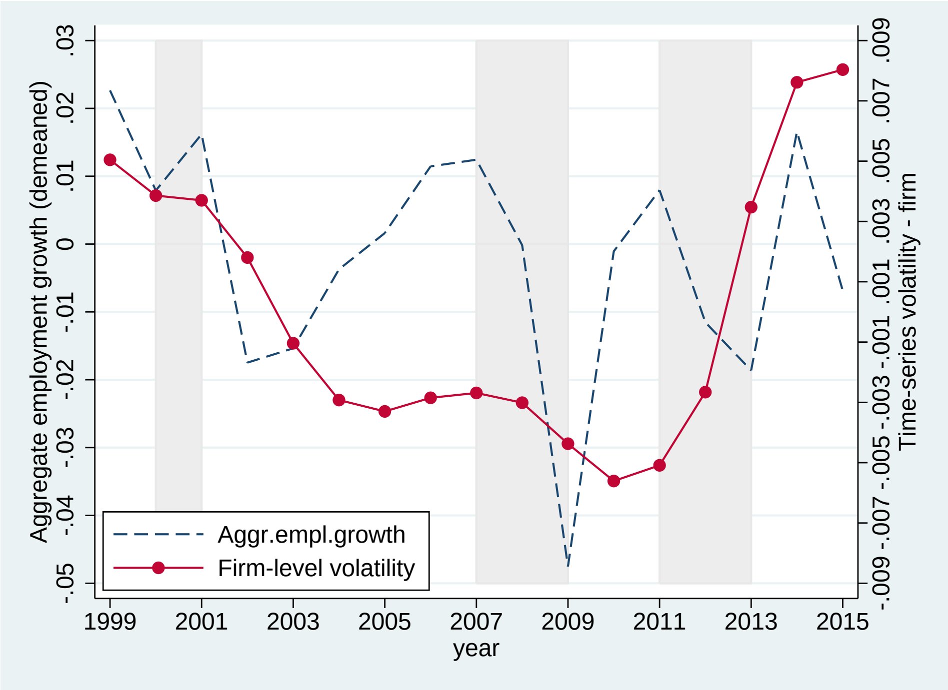
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

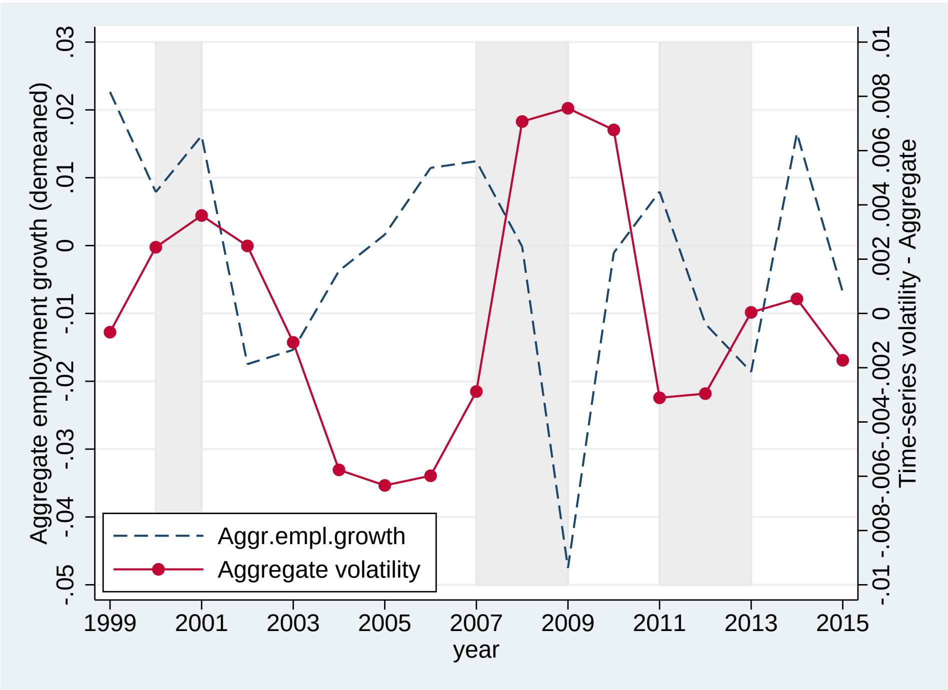
Note: The table displays the longitudinal volatility and skewness measures at various levels of aggregation. For the first column, we calculate the measures for each firm, and report the average. For the second and third columns we calculate the measures at the corresponding industry levels, and report the averages. For the aggregate measure, we calculate the measures at aggregate level, and report the average.

TO BE COMPLETED

In sum, contrary to the stylized fact of a countercyclical volatility and negative skewness of aggregate economic outcomes established in the literature, we document pro-cyclical volatility and positive skewness for employment growth in Belgium. Given the institutional environment, the results are consistent with the mechanism described. Further, we study productivity distribution in the cross-section and time-series to make sure that the asymmetric responses are not driven by asymmetric shocks.

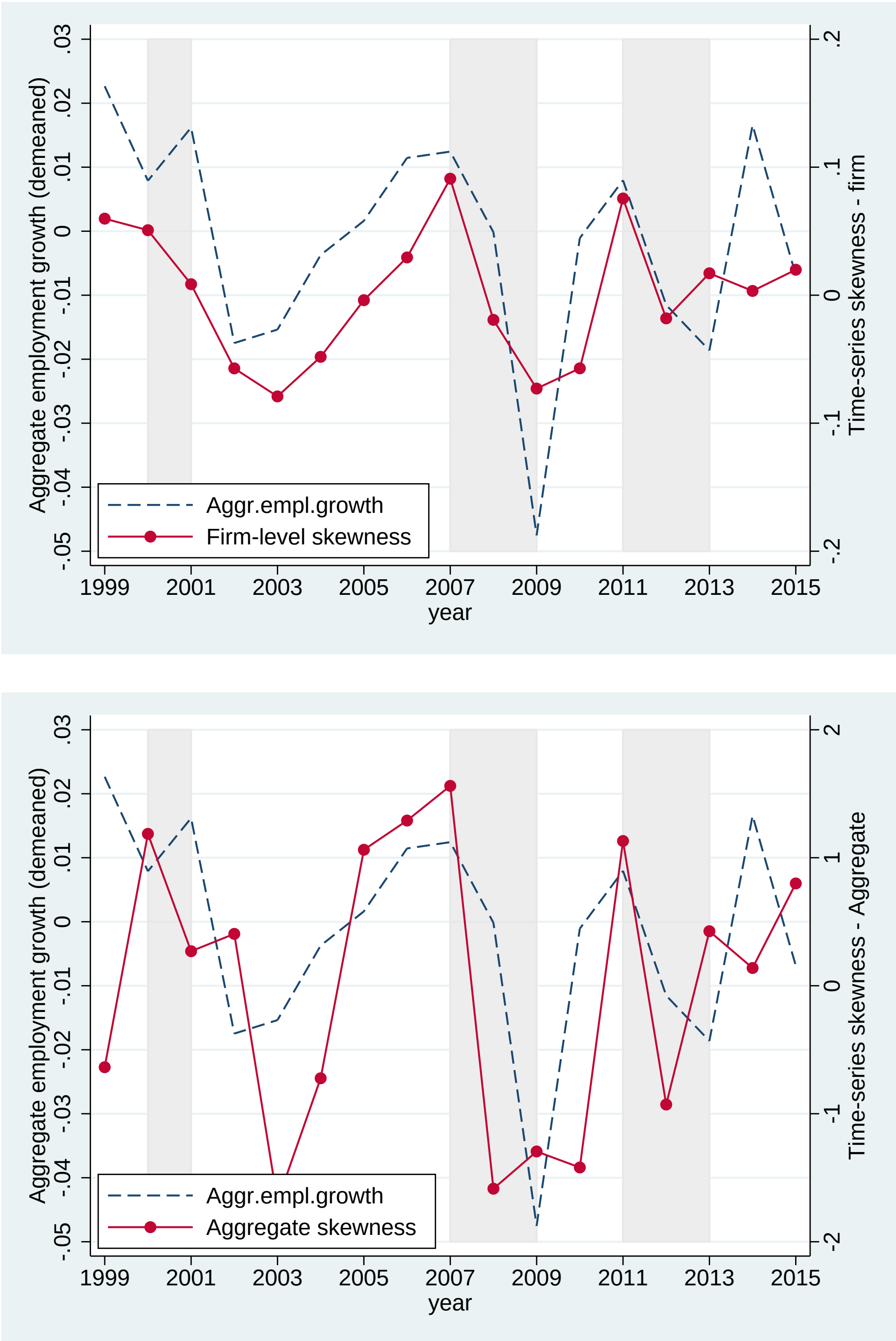
Figure 4: Time-series volatility





Note: On the right axis, this figure displays the year-by-year time-series volatility measure, Vol_t^i, of employment growth. The top panel shows the volatility at firm level. The bottom panel shows the volatility at the aggregate level. On the left axis, the gray dashed line represents demeaned aggregate employment growth. OECD recessions are marked by the vertical gray bars.

Figure 5: Time-series skewness



Note: On the right axis, this figure displays the year-by-year time-series skewness measure, $Asym_t^i$, of employment growth. The top panel shows the skewness at firm level. The bottom panel shows the skewness at the aggregate level. On the left axis, the gray dashed line represents demeaned aggregate employment growth. OECD recessions are marked by the vertical gray bars.

Productivity Distribution in Cross-Section and Time-Series

Begin by deriving the Solow residual for every firm i in year t from the Cobb-Douglas production function (in logs):

$$va_t^i = sr_t^i + \beta^k k_t^i + \beta^l l_t^i, \tag{10}$$

where va_t^i is production (value added), k_t^i and l_t^i are real inputs of capital and labor measured by tangible fixed assets and average number of workers in full-time equivalents, respectively, and sr_t^i is the Solow residual. The production elasticities of labor and capital inputs are the median revenue shares of respective factors. Using a more sophisticated TFP estimation (OP, LP, ACF) requires some timing assumptions about the arrival of the information and the choice of inputs, which might potentially conflict with the timing assumptions of the proposed mechanism, where choices are based on current signals. The β^x-s are specific to NACE Rev.2 three-digit industry level. This allows for rich heterogeneity in elasticities and at the same time leaves enough observations per industry for reference.

Ultimately, we are interested in TFP shocks. Assume that the Solow residual contains an aggregate growth trend, common and firm-specific fixed effects, and a stationary component:

$$sr_t^i = gt + \bar{A} + \alpha^i + Z_t^i, \tag{11}$$

where g is long-run industry specific growth rate, $\bar{A}$ is initial technology level (common industry component), α^i is firm specific-fixed effects. The distribution of Z_t^i over time is assumed to be stationary with mean zero. After detrending the residual and imposing an AR(1) assumption on Z_t^i:

$$\begin{aligned} X_t^i &\equiv sr_t^i - gt - \bar{A} = \alpha^i + \rho Z_t^i = \alpha^i + \rho Z_{t-1}^i + z_t^i, && (12)\\ &= \alpha^i(1-\rho) + \rho X_{t-1}^i + z_t^i = \alpha^i(1-\rho) + \rho X_{t-1}^i + u_t^a + u_t^i. && (13) \end{aligned}$$

Predict the TFP shock, z_t^i, from the above equation with panel fixed-effect regression.

The model predicts that convex/concave responses to TFP shocks induce positive/negative skewness. If TFP shocks are the only source of variation, then employment growth should exhibit more skewness and cyclical volatility than the shocks themselves. Table 4 reports the summary statistics of cross-sectional moments for TFP innovations and employment growth. By construction, the mean of TFP innovation is zero. The main finding is that TFP innovations are less positively skewed compared to the employment growth. With both measures of skewness, TFP innovation is negatively skewed, while employment growth is positively skewed. Standard deviation of TFP innovation is smaller than that of the employment growth. Both average interquartile and interdecile ranges of TFP innovation are greater than that of the employment growth, which can be explained by the long tails of TFP distribution and the measures being prone to "outliers". Overall, the results indicate that asymmetric hiring and firing behaviour are not due to asymmetries in TFP shocks.

Table 4: Cross-sectional moments summary

Moment	TFP Innovation, z_t^i	Employment growth, n_t^i
Mean	0	0.024
Standard deviation	0.293	0.326
Interquartile range	0.290	0.175
Interdecile range	0.653	0.586
Skewness	-0.674	0.024
Kelly Skewness	-0.050	0.128
No. observations	2,070,883	2,113,246

Note: The table displays summary statistics for TFP innovations and employment growth rates. First, cross-sectional measures are computed for every year and then averaged across years.

TO BE COMPLETED

Employment Growth and TFP Innovations

Now we examine average response of employment growth to TFP innovations. Non-parametrically estimate

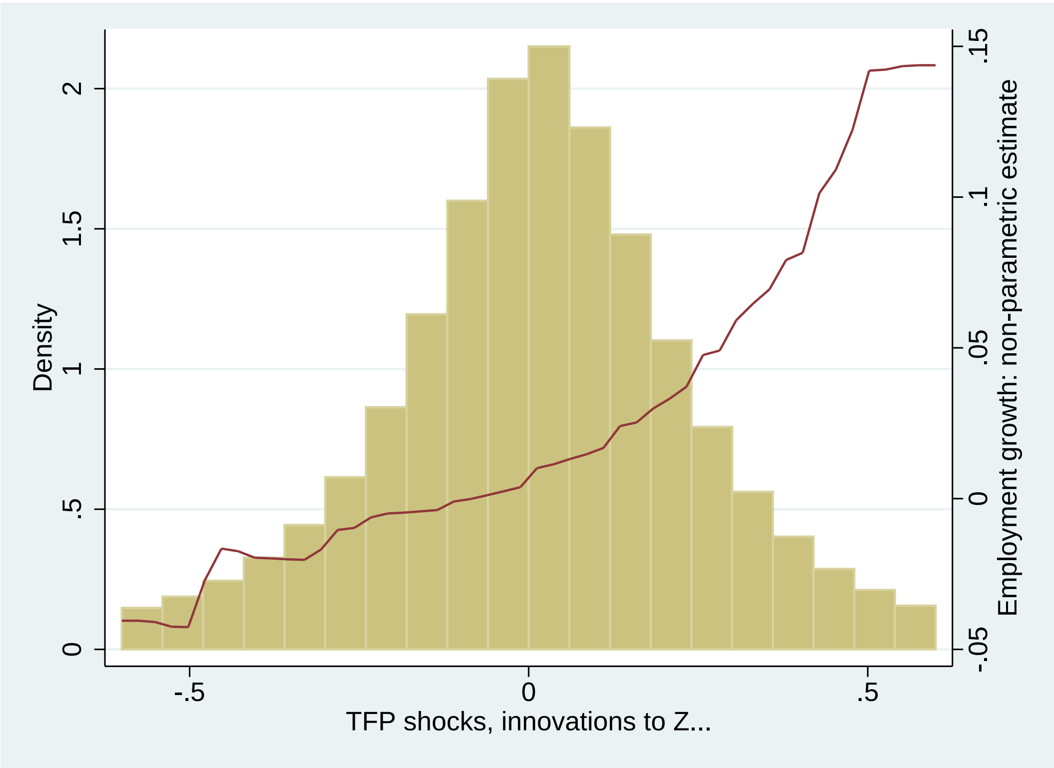
$$n_t^i = g(z_t^i). \tag{14}$$

To address the possible bias from other state variables, we partition the data into subsamples by firm size , and estimate the above equation for each subsample.[7]

[7] Micro = (0,10); small = [10,50); medium = [50,100); large = [100+).

We then aggregate the estimates for each subsample into the representative estimate (average). Figure 6 displays the nonparametric estimate. The estimated regression line corresponds to the function $g(\cdot)$, which reflects the recovered employment growth given the TFP innovation. The solid line displays the mean employment change. The main result is that employment growth responds in a different way to positive and negative shocks. Moreover, the shape of asymmetry is convex over the domain of TFP innovations. After a one standard deviation TFP shock (+0.22) employment growth by 2.3 percent, and decreases by -1.3 percent for a one standard deviation negative shock (-0.22).

Figure 6: Employment growth and TFP innovations



5 Further steps

Sectoral analysis

For designing proper policies, it is required to distinguish between the changes in employment that occur due to business cycles, that potentially affect all sectors of the economy, and the ones that happen due to structural reallocation in production, that affect only particular sectors (Rissman, 2009). Therefore, we will test whether the patterns found in the baseline results hold for broad categories of sectors in the economy: Trade vs. Industry vs. Services.

Type of labor force

Goux et al. (2001) show that the asymmetry between hiring and firing costs is more important for non-production workers, rather than production workers. Moreover, until recently, Belgium employment law was favoring white-collar workers more compared to blue-collar. White-collar workers were experiencing stronger labor market protections, i.e. firing costs for white-collar workers were higher than for blue-collar workers. In this regard, we would like to differentiate between the industries based on the production worker intensity. This will add additional evidence on the importance of the labor market policies in reducing or stressing the effect of business cycles.

Firm characteristics

Apart from size, other firm characteristics play a crucial role in employment dynamics and hiring and firing behavior. In this context, as argued by Haltiwanger et al. (2013), young firms tend to exhibit high rates of job creation and destruction since they can easily adjust through a learning-by-doing mechanism. Moreover, Dhyne et al. (2010) found that multinational firms differ in their employment adjustment from the domestically owned firms. Therefore, it is important to identify what firm characteristics might affect the curviture, i.e. using different data cuts identify what type of firms have more or less convex shape. This will also allow to design specific policies targeting particular firms.

Robustness checks

- Weighted dispersion and skewness
- Davis and Haltiwanger (1992) measure of employment growth
- Robustness with other parametric regressions

- Test that the convex hiring rule is enough to generate the patterns

6 Conclusion

TO BE COMPLETED

References

Abowd, J. M. and F. Kramarz (2003). The costs of hiring and separations. *Labour Economics 10*, 499–530.

Auerbach, A. J., Y. Gorodnichenko, and D. Murphy (2019). Macroeconomic frameworks. *NBER Working Paper No. 26365*.

Bachmann, R. and C. Bayer (2014). Investment dispersion and the business cycle. *American Economic Review 104*(4), 1392–1416.

Bachmann, R., R. J. Caballero, and E. M. Engel (2013). Aggregate implications of lumpy investment: New evidence and a DSGE model. *American Economic Journal: Macroeconomics 5*(4), 29–67.

Berger, D. and J. Vavra (2019). Shocks versus responsiveness: What drives time-varying dispersion? *Journal of Political Economy 127*(5), 2104–2142.

Bijnens, G. and J. Konings (2018). Declining business dynamism in Belgium. *Small Business Economics*, 1–39.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018). Really uncertain business cycles. *Econometrica 86*(3), 1031–1065.

Davis, S. J. and J. Haltiwanger (1992). Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics 107*(3), 819–863.

Decker, R., J. C. Haltiwanger, R. S. Jarmin, and J. Miranda (2018). Changing business dynamism and productivity: Shocks vs. responsiveness. *NBER Working Paper No.24236*.

Dhyne, E., C. Fuss, and C. Mathieu (2010). Labour demand adjustment: Does foreign ownership matter? *NBB Working Paper No. 207*.

Ferraro, D. (2018). The asymmetric cyclical behavior of the US labor market. *Review of Economic Dynamics 30*, 145–162.

Goux, D., E. Maurin, and M. Pauchet (2001). Fixed-term contracts and the dynamics of labour demand. *European Economic Review 45*(3), 533–552.

Haltiwanger, J., R. S. Jarmin, and J. Miranda (2013). Who creates jobs? small versus large versus young. *The Review of Economics and Statistics 95*(2), 347–361.

Haltiwanger, J., S. Scarpetta, and H. Schweiger (2014). Cross country differences in job reallocation: The role of industry, firm size and regulations. *Labour Economics 26*, 11–25.

Higson, C., S. Holly, P. Kattuman, and S.Platis (2004). The business cycle, macroeconomic shocks and the cross-section: The growth of UK quoted companies. *Economica 71*(282), 299–318.

Ilut, C., M. Kehrig, and M. Schneider (2018). Slow to hire, quick to fire: Employment dynamics with asymmetric responses to news. *Journal of Political Economy 126*(5), 2011–2071.

Kehrig, M. (2015). The cyclical nature of the productivity distribution. *Earlier version: US Census Bureau Center for Economic Studies Paper No. CES-WP-11-15*.

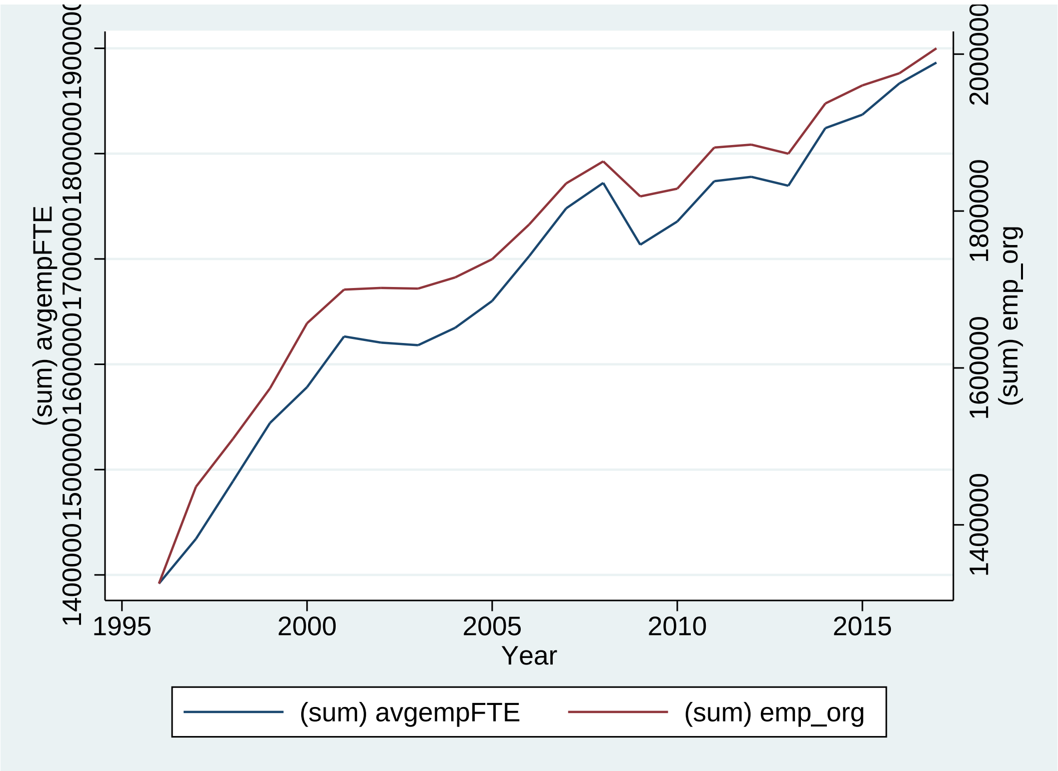
Kramarz, F. and M.-L. Michaud (2010). The shape of hiring and separation costs in France. *Labour Economics 17*, 27–37.

Rissman, E. R. (2009). Employment growth: Cyclical movements or structural change? *Economic Perspectives 33*(4), 40–57.

Appendix

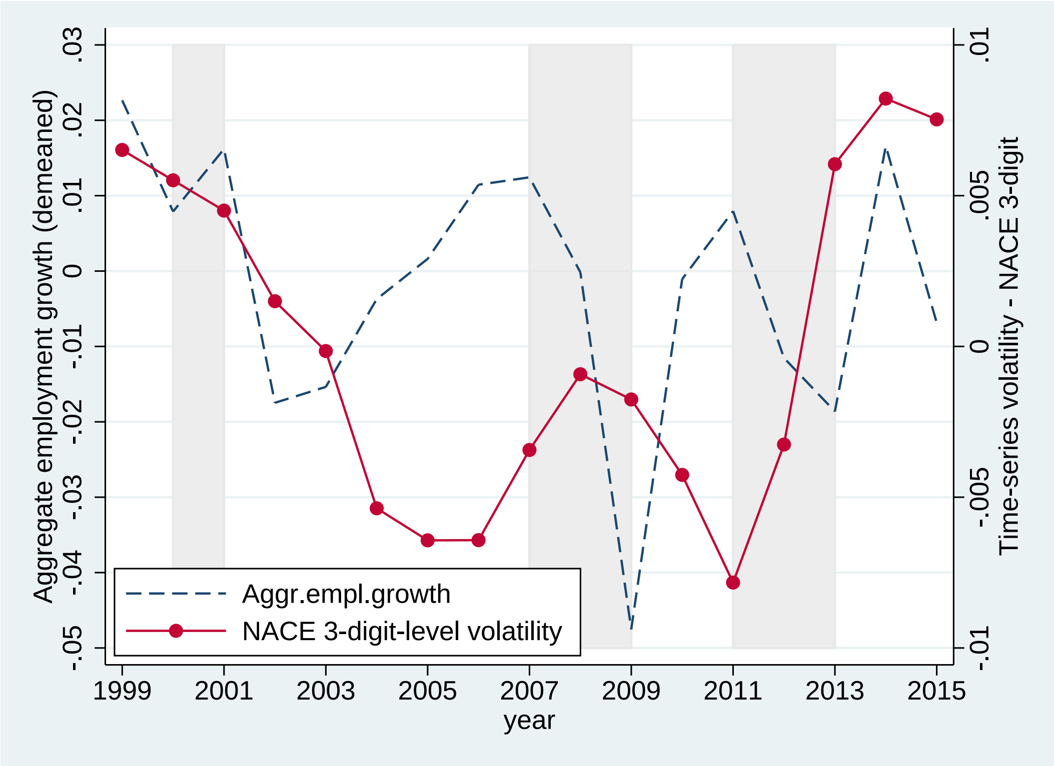
A Additional Figures and Tables

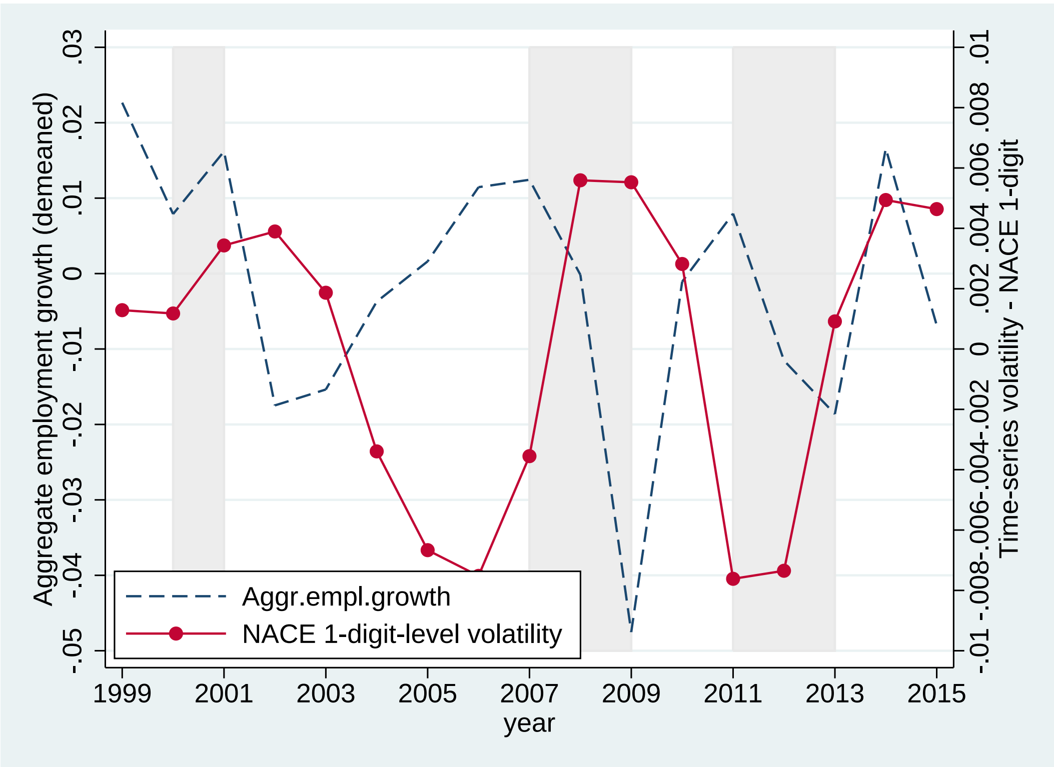
Figure A.1: Aggregate employment



Note: The figure presents the evolution of aggregate employment from the original data and after the cleaning introduced.

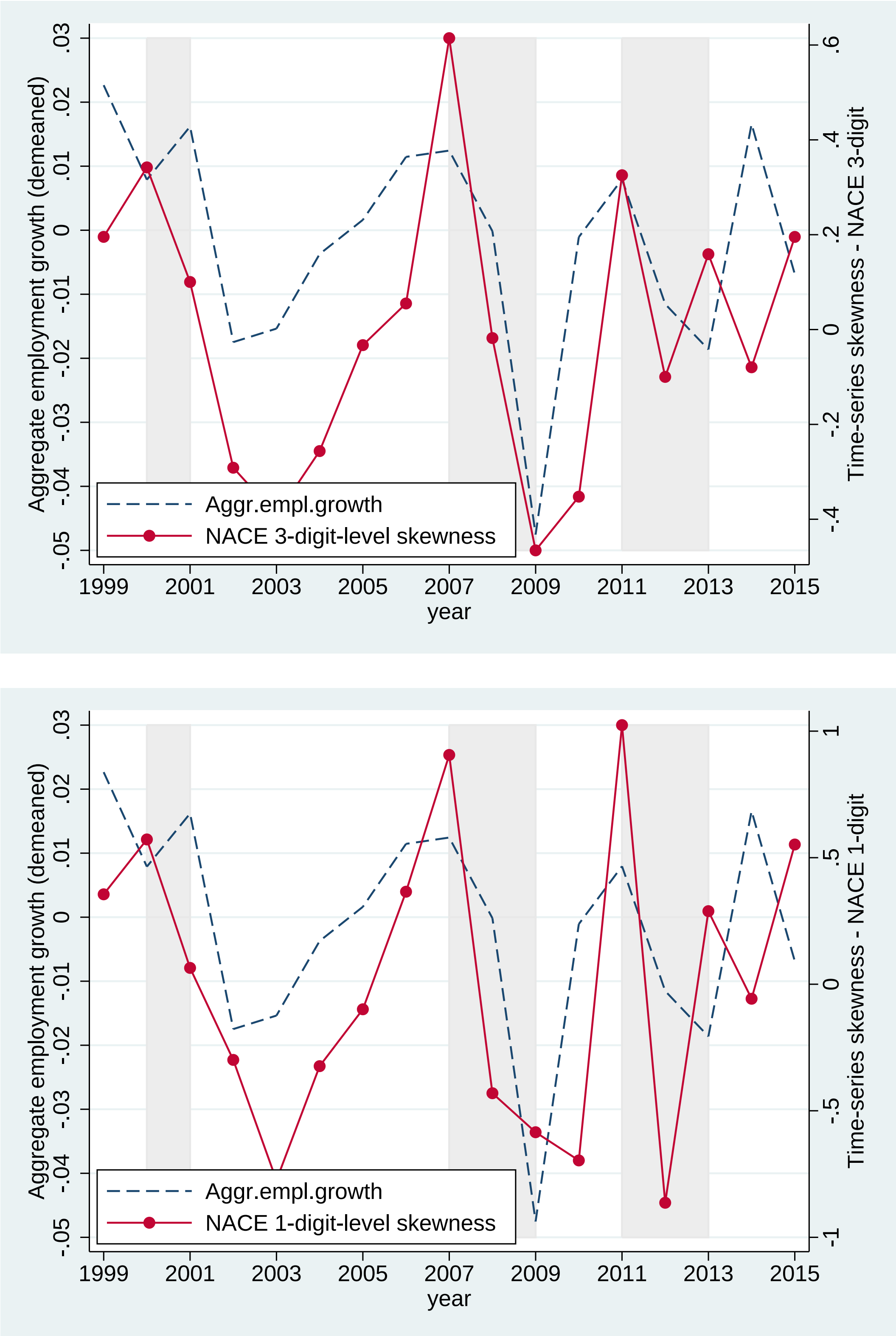
Figure A.2: Time-series volatility





Note: On the right axis, this figure displays the year-by-year time-series volatility measure, Vol_t^i, of employment growth. The top panel shows the volatility at NACE three-digit level. The bottom panel shows the volatility at NACE one-digit level. On the left axis, the gray dashed line represents demeaned aggregate employment growth. OECD recessions are marked by the vertical gray bars.

Figure A.3: Time-series skewness



Note: On the right axis, this figure displays the year-by-year time-series skewness measure, $Asym_t^i$, of employment growth. The top panel shows the skewness at NACE three-digit level. The bottom panel shows the skewness at NACE one-digit level. On the left axis, the gray dashed line represents demeaned aggregate employment growth. OECD recessions are marked by the vertical gray bars.