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Abstract

Variations in the unemployment rates of men and women often differ markedly. To understand the dynamics of the gender unemployment gap, this paper estimates the inflows to, and outflows from, unemployment by gender for 18 OECD countries over the last four decades. Whilst there are are cross-country differences in the relative contribution of inflows and outflows by gender, there is a clear common pattern: differences in the variations of the *inflow* of unemployment explain the majority of the dynamics of the gender unemployment gap for all countries under study. Specifically, in the recessions covered by our data, the flow of males into unemployment is typically larger than the flow of females into unemployment. Using data on output by sector, we show that a candidate explanation for these results for each country is the differing gender composition by sector. Over the four decades of data we analyse, and across all countries, females were more likely to work in sectors less exposed to economic downturns.

Keywords: Unemployment, gender, inflows, outflows, dynamics
JEL codes: E24, E32, J16, J6

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Non-technical summary

Variation in the unemployment rate tends to differ markedly for males and females. Using data for 18 countries over four decades, we show that this stylised fact is evident in a large number of countries over a long time-period.

Understanding why this pattern exists is key to informing gender-based policy responses to unemployment. In this paper we decompose variation in the unemployment 'gap' – the difference between male and female unemployment rates – into differences in *inflows* to and *outflows* from unemployment by gender.

Using the decomposition, we show that differences in the variations of the *inflow* of unemployment explain the majority of the dynamics of the gender unemployment gap for all 18 countries we examine. In fact, more than 80% of dynamics of the unemployment gap is explained by differences in the variations of the inflows for 14 of the 18 countries.

We focus in on sub-periods in the data, to see which of the flows contributed to any disproportionate changes in the unemployment rates by gender at specific times. We show that the larger rise in the inflows into unemployment for males is the main explanation for the rise in the gender unemployment gap during the 1991 recession and the Great Recession. For many, but not all, countries, the contribution of gender differences in the outflow from unemployment to gap is negative. This means that, if the outflows for males followed the same pattern as the outflows for females, all else the same, then the rise in the gender unemployment gap during recent recessions would have been larger.

Using data on output by sector and male sector share, we show that sectors that employ more males, seem to be more susceptible to economic swings. This is a consistent result across all countries. Thus, a candidate explanation for cyclical increases in the unemployment gap is that males tend to sort into sectors where output and employment declines more in recessions. Early data from the COVID-19 recession in 2020 suggests a potential reversal of this pattern, with more female dominated jobs in services seeing larger falls in labour demand. As a result, the 2020/21 recession maybe one of the few occasions where the male-female unemployment gap declines, and perhaps turns negative, following a downturn.

1 Introduction

Why do recessions impact males and females differently? This question drew a lot of attention in the media in the US following the Great Recession, as the unemployment rate rose significantly more for males over females.[1] A stronger increase in male unemployment is not unique to the Great Recession in the US and, in fact, similar patterns, but to varying extents, seem to be present in many other developed economies.[2] For example, over the last 4 decades, for Australia, Denmark, France, Spain and the US, the variance of the percentage change in unemployment is over twice as large for males than for females, but only slightly larger for Japan and New Zealand (see Table 1).

The disparity in unemployment dynamics between genders are due to a combination of two forces, differences in the variations of the flows *into* unemployment (variations in the 'inflow gap'), and differences in the variations of the flows *out of* unemployment (variations in the 'outflow gap'). Understanding which of these forces is most important can shed light on the underlying causes of the asymmetric gender impact of recessions, and may inform future gender-based analysis of labour markets and policy making. In this paper, we quantify the role of both of these forces for a large group of countries over a long period using publicly available data.

TABLE 1: Variance of male relative to female unemployment change

	Aus	Bel	Can	Den	Fra	Ger	Ire	Ita	Jap
$\frac{var(\Delta log(u_M))}{var(\Delta log(u_F))}$	2.97	1.64	1.93	2.87	2.17	1.39	1.58	1.71	1.27
	Lux	Neth	NZ	Nor	Por	Spa	Swe	UK	US
$\frac{var(\Delta log(u_M))}{var(\Delta log(u_F))}$	0.96	1.60	1.24	1.58	1.91	2.30	1.37	1.75	2.10

Source: OECD (2018a). Annual data over the last 4 decades. See Table 2 for the exact periods.

We use harmonised data from the Organisation for Economic Cooperation and Development (OECD) to estimate the ins and outs of unemployment by gender for 18 countries over the last four decades for most countries. Using the unemployment flows, we perform a non-steady-state decomposition of unemployment variation for both genders, and for variations in the 'gender unemployment rate gap'; that is: the percentage change in the male unemployment rate minus the percentage change in the female unemployment rate. The results indicate that for all countries, the dynamics of the gender unemployment gap can be predominantly explained by variations in the inflow gap. To understand why male unemployment rates tend to rise proportionately more in recessions, therefore, one must pay close attention to why the percentage increase in the male inflow rate is greater

[1]See articles from the Economist and The New York Times.

[2]A large amount of studies, predominantly in the US and UK, have noted that the male unemployment rate is significantly more volatile than the female unemployment rate. See Clark (1980), Blank (1989), Peiro (2012), Hoynes (2012), Razzu and Singleton (2016) and Albanesi and Sahin (2018) for examples.

than the percentage increase in female inflow rate. We provide evidence that gender composition by sector is one explanation for this result. There has been a tendency to treat unemployment inflows as irrelevant in the US following the influential work of Hall (2005) and Shimer (2012). Yet, when concerning the dynamics of the gender unemployment gap, in fact the opposite is true for all countries under study.

In Section 2, we outline the derivation of the aggregate unemployment flows using data on unemployment duration from the OECD. When constructing unemployment flows using OECD data following Shimer (2012), the estimates can become very noisy for countries with slow moving labour markets. This is especially the case when splitting the data by gender. To rectify this issue, following Elsby et al. (2013), we use all of the available OECD data on unemployment *duration* to create a weighted average of derived flow rates.[3] The gender unemployment flows show interesting commonalities by country. For all countries, apart from Germany and Norway, inflows into unemployment are on average larger for females than for males, but the relative size of the outflows are varied. In all Anglo Saxon countries, females experience higher rates of movements out of unemployment compared to males. This is not true, however, for Continental European and Nordic countries with some experiencing faster movements out of unemployment for women and some for men. On average, among all countries, females have higher transition rates into and out of unemployment. Regarding *changes* in the unemployment flows between 2007 and 2009, for all countries apart from France, the percentage increase in the unemployment inflow is larger for males than for females, but the percentage fall in the unemployment outflow does not follow a similar clear pattern.

Using the estimated flows, we perform a non-steady-state variance decomposition of unemployment variation by gender. This allows us to decompose variations in the gender unemployment gap. In line with Elsby et al. (2013), who focus on all workers, we find that the relative contributions of the ins and outs differ markedly between countries. For example, for Netherlands and Italy, the outs of unemployment for males drive 14% and 76% of unemployment variation, respectively. The ins (outs) of unemployment contribute more (less) to unemployment variation for males than for females for two thirds of the sample. The only countries that clearly depart from this pattern are either Continental European or Nordic. As an example of how different the picture can be between genders, in the UK, the inflow:outflow contribution for males and females is 43:57 and 83:21, respectively - for males, the ins and outs are equally important, while for females the outs of unemployment drive the vast majority of unemployment dynamics. The results indicate that male and female unemployment dynamics can be very different.

Despite the fact that we find different contributions of ins and outs for the variation in unemployment of males and females between different countries, when we look at the *dynamics of the gender unemployment gap* a clear and consistent pattern emerges across all countries in our sample. Variations in the inflow gap, drives the majority of the dynamics

[3] The OECD provides information on the stocks of the unemployed with duration of less than one, three, six and twelve months.

of the gender unemployment gap. In fact, more than 80% of dynamics of the gender unemployment gap is explained by variations in the inflow gap for 14 of the 18 countries. Focusing on the Great Recession, the percentage rise in unemployment relative to 2007 is larger for males than for females for almost all countries. Using the decomposition framework, we show graphically, that the increases in the gender unemployment gap during the 1991 recession and Great Recession are predominantly due to a larger increase in inflows for males than for females for most countries.

In Section 5 we take a step back and ask what the underlying story is behind these results. We focus on the role of the male-female sector composition. To be precise, we ask the following question: What is the relationship between the male sector share, and the cyclicality of that sectors output? We compile sector specific data from the OECD (and BLS for the US) on output and sectoral composition, and find a consistent stylised fact for all countries. There is a positive relationship between the male sector share and the correlation of sector output with overall output. This stylised fact provides a candidate explanation for the results documented in the paper. Males tend to sort into sectors that are more susceptible to cyclical economic swings. This, in turn, increases the average precarity of male jobs in recessions relative to females.

A large body of work has focused on understanding the changes in unemployment flows – both in- and out-flows – from the perspective a representative worker.[4] Despite a lot of media attention regarding changes in the disparity in gender unemployment during the Great Recession, the literature is relatively sparse when it comes to the ins and outs of unemployment by gender.[5] Albanesi and Sahin (2018) study changes in the gender unemployment gap in the US. They show that (among other things) approximately half of the increase in the gender unemployment gap during recessions can be attributed to differences in industry composition by gender. This final observation aligns with the results in this paper, as described above, albeit for a wider sample of countries.

Razzu and Singleton (2016) study the dynamics of UK and US unemployment using a flows based approach. They show that differences in the variations of transitions at the participation margin explain a non negligible proportion of the dynamics of the unemployment gap. Koutentakis (2015) estimates the ins and outs of unemployment for ten OECD countries by gender in a similar manner as we do in this paper.[6] He does not focus on the dynamics of unemployment over the business cycle, but instead asks why the unemployment rate is greater for females than males in some countries. He argues that the steady-state female relative to male unemployment rate is positive for some countries

[4] Perry (1972), Darby et al. (1985), Darby et al. (1986), Davis and Haltiwanger (1992), Hall (2005), Bachmann (2005), Petrongolo and Pissarides (2008), Nagypal (2008), Elsby et al. (2009), Elsby et al. (2010), Fujita and Ramey (2009), Elsby et al. (2011), Smith (2012), Shimer (2012), Gomes (2012) and Simmons (2019) to name a few.

[5] There is clearly a vast literature studying gender disparities in other labour market variables, such as the wages and hours worked, and how these vary over time and between countries. See Olivetti and Petrongolo (2008, 2014, 2016) for a review and examples of the literature.

[6] Although he does not make use of all available data on unemployment durations.

predominantly because of larger unemployment inflows for females. While this is also interesting, it does not say anything with regards to the origins of the asymmetric impact that recessions have by gender, to which this study is focused.

In this paper, we only consider a two-state world (employment or unemployment), which does not allow us to look at the participation decision. One clear advantage of using a two-state approach is that it allows for the study of a larger group of countries over a longer period (using harmonised OECD data) than would otherwise be possible. The disadvantage is that it overlooks the particpation margin. In Section 6, we consider the implications for the analysis. Using data on flows at the participation margin from micro data sourced for a sub-sample of countries. We show that avoiding non-participation is not likely to significantly affect the results. Further robustness analysis looks at the sensitivity of our results to using *logarithmic* deviations in the unemployment gap. Using non-logarithmic deviations in the unemployment gap, we find qualitatively similar results.

The remainder of this paper is structured as follows. Section 2 outlines the derivation of the flow rates. Section 3 describes the non-steady-state variance decomposition of unemployment and the gender unemployment gap, and Section 4 describes the results. Section 5 shows that a candidate explanation for differing dynamics of male and female unemployment is due to sector composition. Section 6 provides presents robustness tests and a discussion. This section includes a discussion on gender unemployment dynamics during the COVID-19 recession. At the time of writing, early data from the COVID-19 recession in 2020 suggests a potential reversal of the pattern of male inflows to unemployment exceeding female inflows in some countries – a pattern driven by the negative impact of restrictions to combat the spread of the virus on activity in more female dominated, often services, sectors. Consequently, the 2020/21 recession maybe one of the few times in the last half-century where the male-female unemployment gap declines, and perhaps turns negative. Finally, Section 7 concludes. A data Appendix provides additional charts and tables; and an online appendix describes in detail the estimation process for unemployment outflows.

2 Estimating unemployment flows with aggregate data

This section outlines the derivation of the unemployment flows, based on Elsby et al. (2013). We focus on 18 OECD countries: Australia, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, the United Kingdom, and the United States, over all the available data. The data covers the last 4 decades or so, ending in 2018 for all countries (see Table 2 for the start year for each country).

The derivation makes use of two different pieces of information. (i) annual unemployment rates, OECD (2018a), and (ii) the annual percentage of the unemployed with less than d months of unemployment duration, given as $u_t^{<d}$, OECD (2018b). To begin,

consider the following description of unemployment variation:

$$\dot{u}_t = s_t(1-u_t) - f_t u_t, \tag{1}$$

where u_t is the unemployment rate at time t, $\dot{u}_t$ is the change in the unemployment rate over one month at time t, s_t is the monthly unemployment inflow rate from employment at time t, and f_t is the monthly unemployment outflow rate into employment at time t.

It is important to stress that s_t and f_t do not represent flows *only* between unemployment and employment. Rather, s_t and f_t are inflated by flows at the participation margin. To see this clearly, notice that the steady state unemployment rate (u_t^*), when $\dot{u}_t = 0$, can be written as

$$u_t^* = \frac{s_t}{s_t + f_t} \equiv \frac{\lambda_t^{eu} + \frac{\lambda_t^{en}\lambda_t^{nu}}{\lambda_t^{ne}+\lambda_t^{nu}}}{\lambda_t^{eu} + \frac{\lambda_t^{en}\lambda_t^{nu}}{\lambda_t^{ne}+\lambda_t^{nu}} + \lambda_t^{ue} + \frac{\lambda_t^{un}\lambda_t^{ne}}{\lambda_t^{ne}+\lambda_t^{nu}}}, \tag{2}$$

where λ_t^{ij} represents transitions from state i to state j at time t, and where e, u and n are employment, unemployment and inactivity. The equivalence between the second and third terms follows from evaluating the economy from a three state perspective. The unemployment inflow rate is a function of flows directly from employment to unemployment, λ_t^{eu}, and indirect flows from employment, through inactivity, and into unemployment, $\frac{\lambda_t^{en}\lambda_t^{nu}}{\lambda_t^{ne}+\lambda_t^{nu}}$. The unemployment outflow rate is a function of flows directly from unemployment to employment, λ_t^{ue}, and indirect flows from unemployment, through inactivity, and into employment, $\frac{\lambda_t^{un}\lambda_t^{ne}}{\lambda_t^{ne}+\lambda_t^{nu}}$. Because of this, we do not refer to s_t and f_t as the job separation and job finding rates. Instead, we use the more accurate terminology of the unemployment inflow rate and the unemployment outflow rate.

Continuing with the estimation method, and recalling the fact that the underlying OECD data is annual, we solve equation (1) forward twelve months to get

$$u_t = \frac{s_t}{s_t + f_t}\left(1 - e^{-12(s_t+f_t)}\right) + e^{-12(s_t+f_t)} u_{t-12}. \tag{3}$$

This describes a recursive relationship between unemployment now and unemployment one year ago. Notice that, $1 - e^{-12(s_t+f_t)}$ converges to 1 as the flow rates increase, which results in the unemployment rate at time t approaching steady-state.[7] This is because the speed of convergence to the limiting distribution of the Markov process is faster the larger the joint level of the flow rates.

Using information provided by the OECD on what percentage of the labour force have been in unemployment for less than one month, $u_t^{<1}$, we can also write a recursive relationship of unemployment as

$$u_{t+1} - u_t = u_{t+1}^{<1} - F_t u_t, \tag{4}$$

[7] See the online Appendix for further details.

where F_t is the monthly outflow probability. Rearranging, the monthly unemployment outflow probability can be written as

$$F_t = 1 - \frac{u_{t+1} - u_{t+1}^{<1}}{u_t}. \tag{5}$$

Assuming that workers leave and enter unemployment following a Poisson point process, the monthly unemployment outflow rate is

$$f_t = -ln(1 - F_t). \tag{6}$$

Finally, using equation (3), s_t can also be solved for numerically.

One issue that arises with estimating unemployment flows using the OECD data in this manner is that for many countries in the sample, few workers are in their first month of unemployment at any one point in time. Or $u_t^{<1}$ can be very small. This can result in noisy estimates of the flow rates for countries with slow moving labour markets. This is especially problematic when splitting the flows by gender as we do in this paper, which reduces the sample sizes. To counteract this, we follow Elsby et al. (2013) and use all the available data on unemployment duration provided by the OECD. See the online Appendix for further information regarding the full estimation process.

Unemployment flows by gender

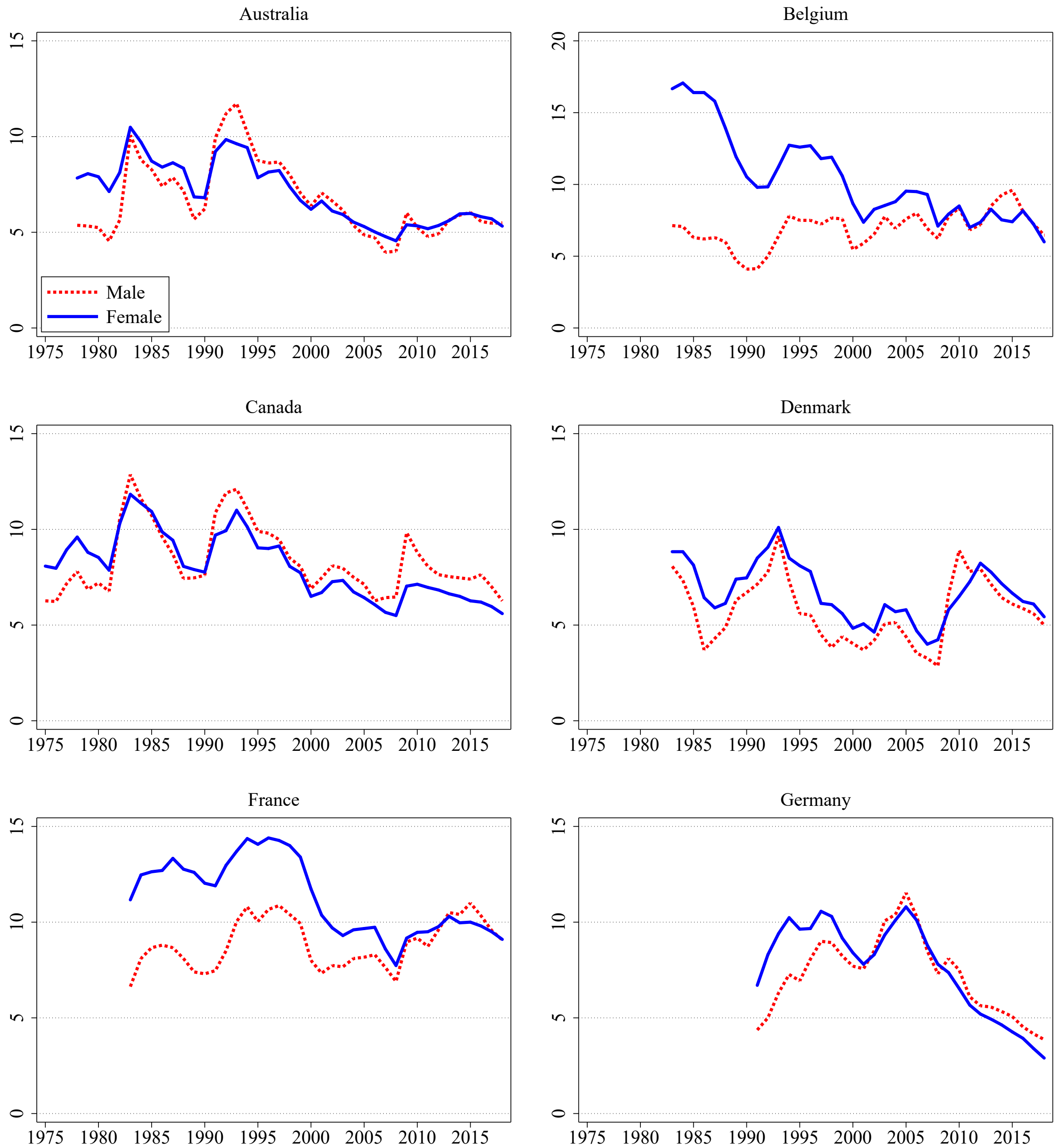
Figure 1 shows the unemployment rates over time for each country. There has been a clear convergence in unemployment rates for Belgium, France, Italy, Netherlands and Spain, during the end of the twentieth and beginning of the twenty first centuries. The country that stands out with regards to the experience during the Great Recession by gender is Ireland. The unemployment rate rose to 18% for males and 13% for females. These disparities in unemployment dynamics are our focus in this paper. Which flow is driving these differences in labour market experience by gender over time?

Figure 2 shows the estimated inflow and outflow rates for each country. In Table 2, we present the main points in order for ease of exposition, showing the average estimated inflow and outflow rates by gender for each of the 18 countries. The magnitudes are very similar to the estimated unemployment flows, not by gender, in Elsby et al. (2013). In line with the findings of Koutentakis (2015), we find that for almost all countries, apart from Germany and Norway, inflows into unemployment are on average larger for females than for males. We do not observe such a clear pattern for the outflows. In Spain, the outflow is on average 28% larger for males than for females; whereas in Ireland, the outflow is on average 37% lower for males than for females. Notice that the for English speaking countries and Japan, there are faster movements for females relative to males in both directions, but that for Continental Europe and Nordic economies the picture is varied. In general, on average, females experience both faster movements into unemployment and faster movements out of unemployment. This an interesting result, but one should not take this to mean that, on average, females are fired at a faster rate than males. There are other reasons as to why workers move into unemployment. Workers may enter the labour force or voluntarily leave their employer. We cannot disentangle between these different types of inflows using the annual OECD data.

On the right side of Table 2, we report the average annual percentage change in the unemployment flows between 2007 and 2009, in order to gauge which flows responded more during the Great Recession. We find stark differences between males and females. For all countries, apart from France, the percentage increase in the inflow was larger for males than for females. This is epitomised by Ireland, where males experienced a 46 percentage point (pp) larger increase in the unemployment inflow relative to females. In fact, on average, the change in the inflow during the most recent recession was actually slightly negative for females, but large and positive for males. With regards to outflows, however, we do not observe a common pattern. The fall in outflows was larger for ten out of the eighteen countries for females and on average the difference in the percentage changes in the outflows is close to zero.

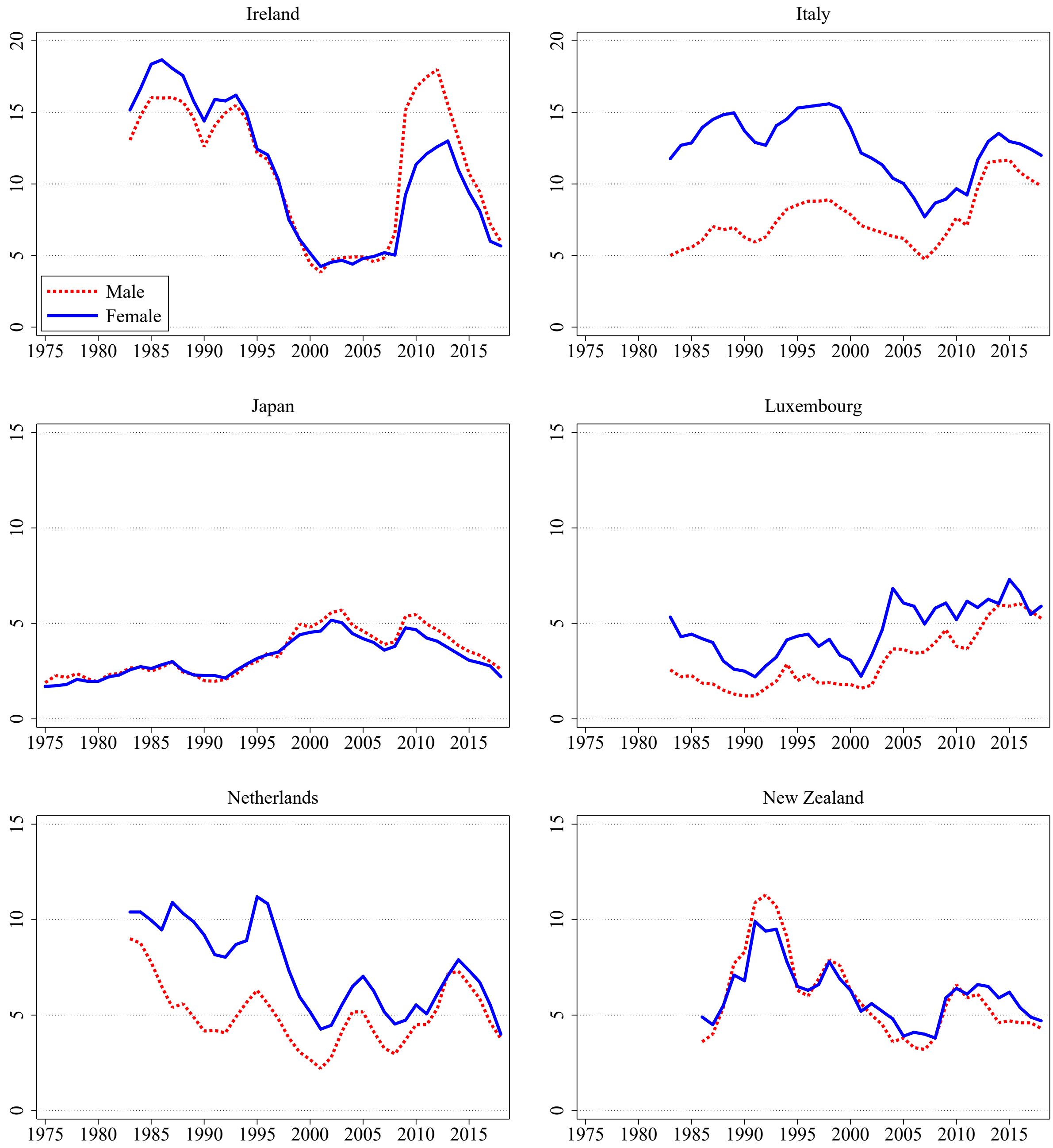
Table 2 is suggestive evidence that variations in the inflows *into* unemployment play a larger role for male unemployment dynamics relative to female unemployment dynamics, and is perhaps the main driver behind different variations in the unemployment gap between countries. These results square well with Hoynes (2012), who shows that males experienced larger increases in the rates of layoff during the Great Recession in the US. In the next section, we formally decompose the dynamics of the gender unemployment gap into components attributed to differences in the variations of the flows into unemployment, and to differences in the variations of the flows out of unemployment.

FIGURE 1: Unemployment rate by gender across the OECD



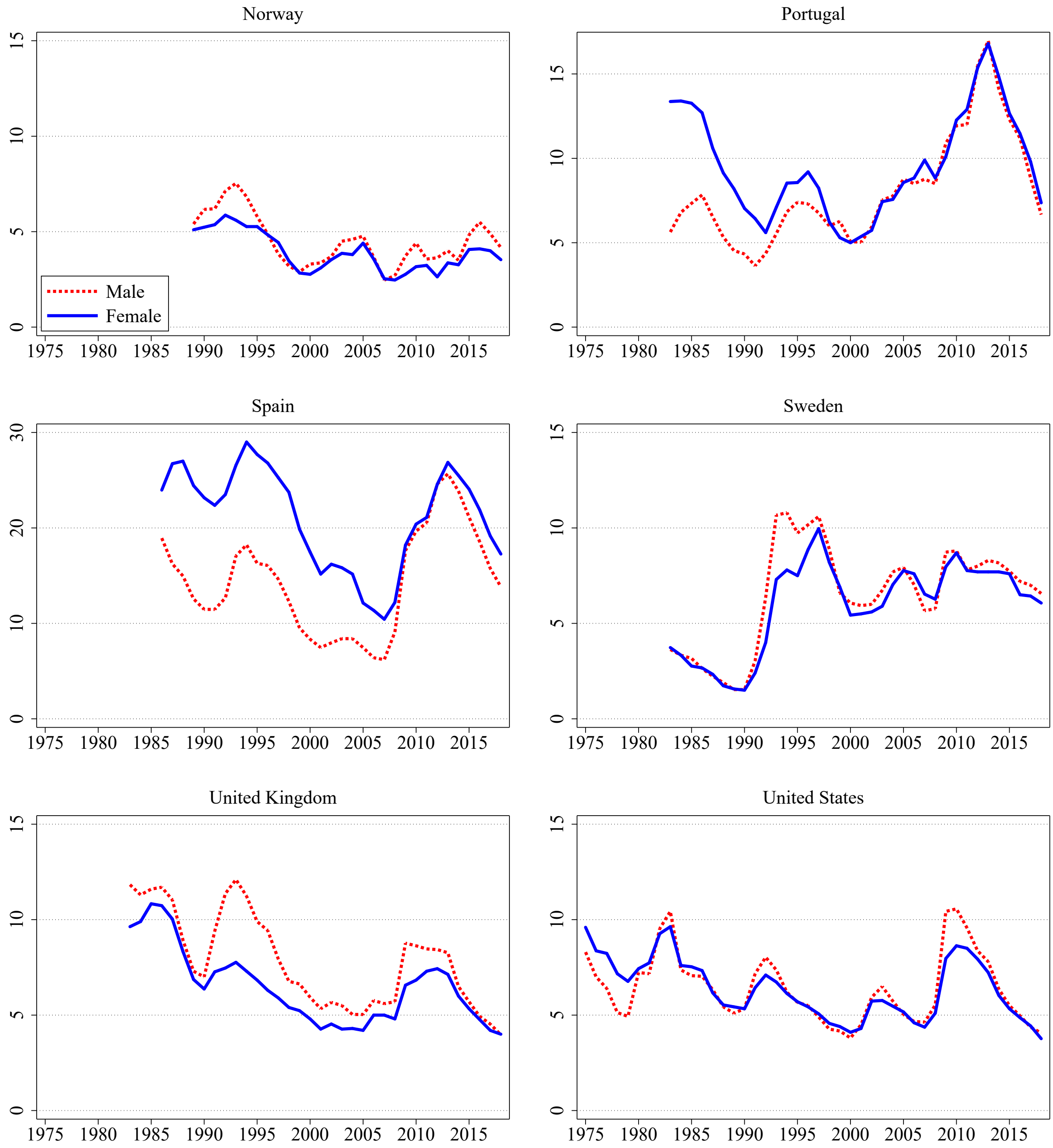
Source: OECD (2018a).

FIGURE 1: Unemployment rate by gender across the OECD (cont'd)



Source: OECD (2018a).

FIGURE 1: Unemployment rate by gender across the OECD (cont'd)



Source: OECD (2018a).

TABLE 2: The average estimates of monthly unemployment flow rates by gender, and changes in the flows during the Great Recession.

		Average monthly flows						Average annual % Δ in flows between 2007 and 2009					
	Start year	s^M	s^F	f^M	f^F	$\frac{s^M}{s^F}$	$\frac{f^M}{f^F}$	s^M	s^F	f^M	f^F	$s^M - s^F$	$f^M - f^F$
Australia	1978	1.79	2.01	24.78	26.68	**0.89**	**0.93**	5.20	1.69	-16.80	-4.86	**3.51**	**-11.94**
Belgium	1984	0.38	0.48	4.90	4.47	**0.79**	**1.10**	7.82	-24.57	-13.03	-13.16	**32.39**	**0.13**
Canada	1976	3.39	3.67	37.70	42.71	**0.93**	**0.88**	7.08	-0.57	-14.07	-10.85	**7.65**	**-3.21**
Denmark	1984	0.72	0.83	12.32	11.92	**0.87**	**1.03**	51.64	12.74	-8.61	-7.99	**38.90**	**-0.62**
France	1975	0.50	0.59	5.06	4.60	**0.85**	**1.10**	-3.33	1.06	-29.96	-21.05	**-4.39**	**-8.92**
Germany	1983	0.49	0.48	6.14	5.85	**1.01**	**1.05**	10.67	-12.02	-2.58	-6.23	**22.68**	**3.65**
Ireland	1984	0.56	0.81	5.01	7.92	**0.69**	**0.63**	62.34	16.72	-33.86	-27.12	**45.61**	**-6.74**
Italy	1983	0.38	0.58	4.48	4.07	**0.65**	**1.10**	16.09	-0.93	-16.26	-21.37	**17.03**	**5.11**
Japan	1977	0.34	0.51	10.68	15.99	**0.68**	**0.67**	20.75	10.73	-11.43	-11.34	**10.02**	**-0.09**
Luxembourg	1984	0.35	0.55	9.56	10.52	**0.64**	**0.91**	39.58	0.88	19.92	-21.72	**38.70**	**41.64**
Netherlands	1985	0.31	0.45	5.74	5.54	**0.70**	**1.04**	12.66	3.61	-13.04	-2.28	**9.05**	**-10.76**
New Zealand	1987	1.09	1.25	14.77	17.66	**0.87**	**0.84**	23.30	12.88	-6.32	-8.31	**10.42**	**1.98**
Norway	1983	0.77	0.74	17.70	19.75	**1.03**	**0.90**	20.24	-9.73	-4.51	-15.05	**29.97**	**10.54**
Portugal	1986	0.57	0.59	6.93	6.03	**0.96**	**1.15**	20.81	-14.88	-3.57	-14.18	**35.69**	**10.61**
Spain	1977	1.35	1.61	8.78	6.84	**0.84**	**1.28**	18.56	-0.40	-56.18	-39.28	**18.96**	**-16.90**
Sweden	1976	0.92	0.93	14.19	14.91	**0.99**	**0.95**	16.92	-4.34	-13.54	-16.26	**21.25**	**2.72**
United Kingdom	1983	0.68	0.76	8.48	11.74	**0.90**	**0.72**	20.79	-2.85	-15.67	-19.41	**23.64**	**3.74**
United States	1969	2.78	3.61	45.46	54.91	**0.77**	**0.83**	11.84	-0.08	-28.88	-29.80	**11.92**	**0.93**
Total average		0.97	1.14	13.48	15.12	**0.84**	**0.95**	20.16	-0.56	-14.91	-16.13	**20.72**	**1.21**

Note: All series end in 2018. Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

3 Decomposition method

This section outlines the decomposition of the non-steady-state variations of unemployment into variations in the two unemployment flows. By taking a log-linear approximation of (3), the non-steady-state logarithmic variations in the unemployment rate can be written as

$$\triangle ln(u_t) = \lambda_{t-12}\{(1-u^*_{t-12})[\triangle ln(s_t) - \triangle ln(f_t)] + \frac{1-\lambda_{t-24}}{\lambda_{t-24}}\triangle ln(u_{t-12})\} + \varepsilon_t, \tag{7}$$

where $\lambda = (1-e^{-12(s_t+f_t)})$. Equation (7) describes a recursive relationship regarding variations in logarithmic unemployment out of steady-state. Notice that, as λ converges to one, the second term within the braces converges to zero and equation (7) collapses to its steady-state counterpart.

The steady-state approximation is used in many papers including Elsby et al. (2009) and Fujita and Ramey (2009). There are, however, two reasons why a non-steady-state version is warrented here. First, assuming that countries with slow flows into and out of unemployment, like many in the sample in this paper, are in steady-state, results in large errors from the decomposition. Second, because unemployment flows are, in general, slightly larger for females than males, the convergence to steady-state should be faster for females and so the errors for males are likely to be larger. In the online appendix we show that both of these assertions are broadly true in the OECD data. To draw comparisons of unemployment dynamics between genders across many countries, therefore, requires a decomposition *out of* steady-state.

Using equation (7), the following measures describing the percentage contributions of four distinct components are calculated

$$\beta_f = \frac{Cov(\Delta ln(u_t), C_{f_t})}{Var(\Delta ln(u_t))},\ \beta_s = \frac{Cov(\Delta ln(u_t), C_{s_t})}{Var(\Delta ln(u_t))},\ \beta_0 = \frac{Cov(\Delta ln(u_t), C_{0_t})}{Var(\Delta ln(u_t))},\ \beta_\varepsilon = \frac{Cov(\Delta ln(u_t), \varepsilon)}{Var(\Delta ln(u_t))}, \tag{8}$$

where

$$C_{f_t} = \lambda_{t-12}\{-(1-u^*_{t-12})\Delta ln(f_t) + \frac{1-\lambda_{t-24}}{\lambda_{t-24}}C_{f_{t-12}}\} \text{ with } C_{f_0} = 0,$$

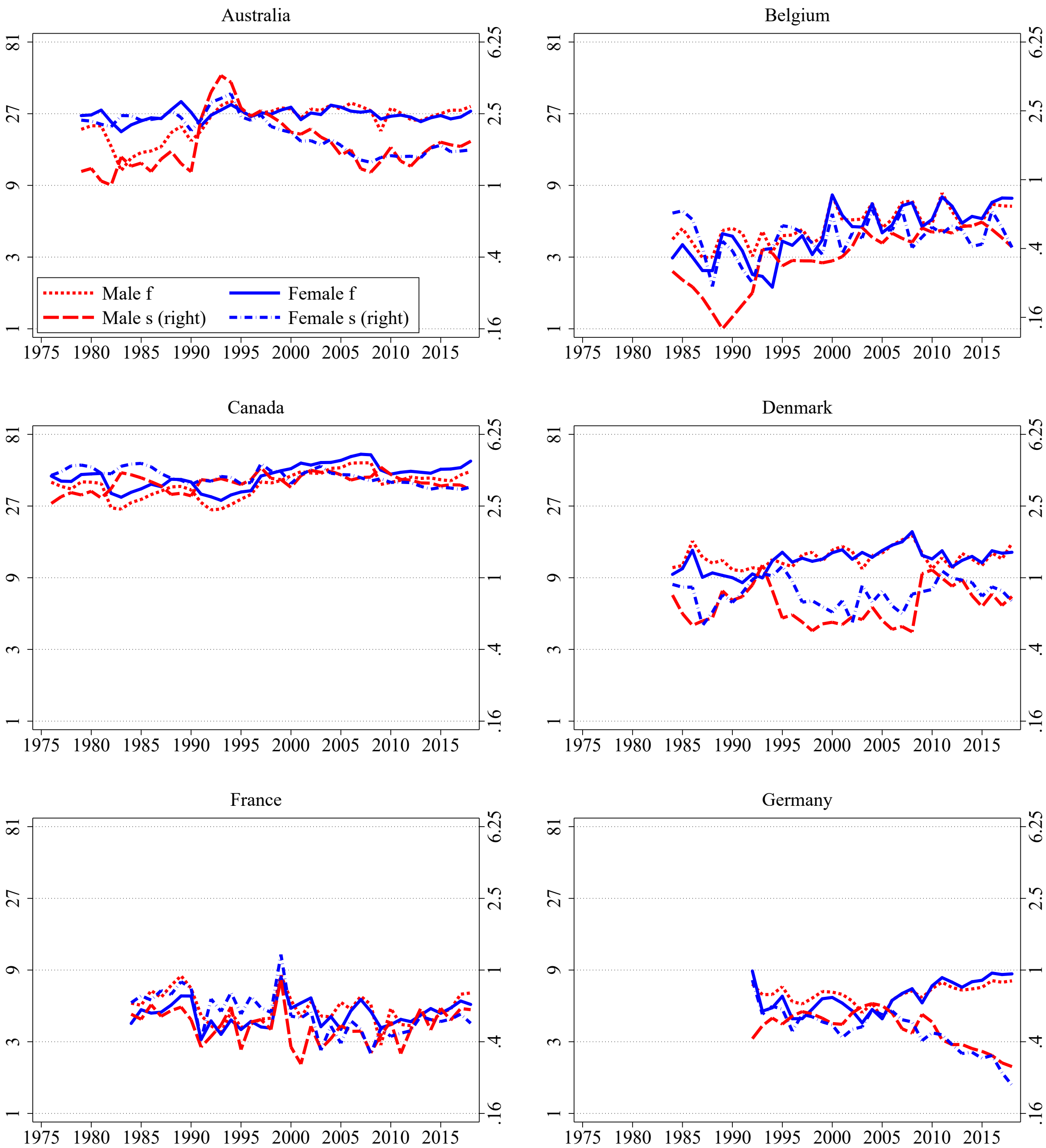
$$C_{s_t} = \lambda_{t-12}\{(1-u^*_{t-12})\Delta ln(s_t) + \frac{1-\lambda_{t-24}}{\lambda_{t-24}}C_{s_{t-12}}\} \text{ with } C_{s_0} = 0,$$

and

$$C_{0_t} = \lambda_{t-12}\frac{1-\lambda_{t-24}}{\lambda_{t-24}}C_{0_{t-12}} \text{ with } C_{0_0} = \Delta ln(u_0).$$

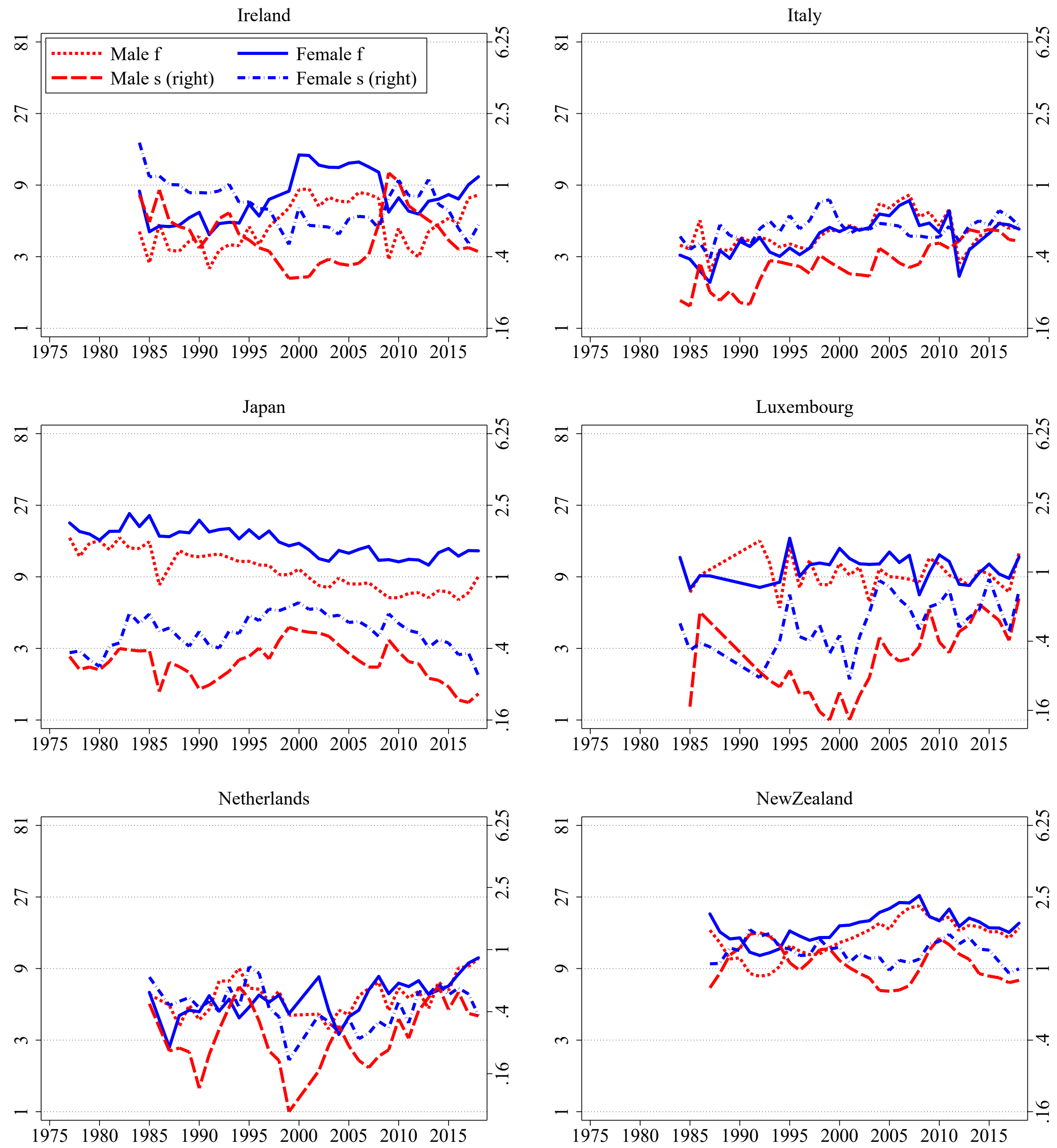
C_{s_t} and C_{f_t} describe the contributions of the contemporaneous and past variations of the ins and outs of unemployment to unemployment variation, respectively. C_0 describes deviations attributable to initial deviations from steady-state. Precisely, β_s and β_f are the percentage contribution of the contemporaneous and past deviations in the ins and outs of unemployment to unemployment variation, respectively. β_0 describes the percentage

FIGURE 2: The percentage estimated monthly inflow and outflow rates by gender across the OECD (log scale)



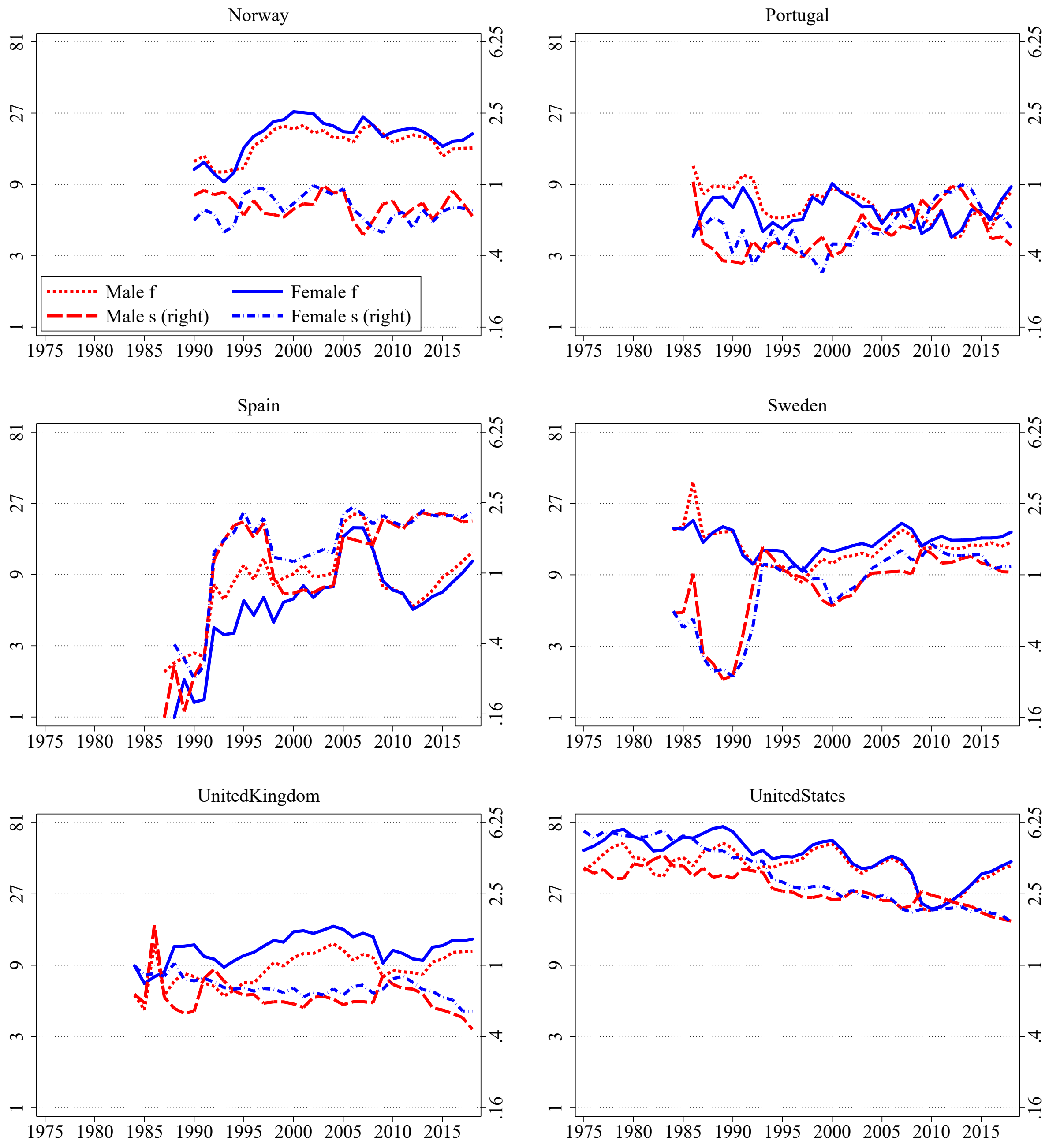
Note: Unemployment outflows (f) on the left hand axis. Unemployment inflows (s) on the right hand axis. Axes are in logarithmic scales.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

FIGURE 2: The percentage estimated monthly inflow and outflow rates by gender across the OECD (cont'd)



Note: Unemployment outflows on the left hand axis. Unemployment inflows on the right hand axis. Axes are in logarithmic scales.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

FIGURE 2: The percentage estimated monthly inflow and outflow rates by gender across the OECD (cont'd)



Note: Unemployment outflows on the left hand axis. Unemployment inflows on the right hand axis. Axes are in logarithmic scales.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

contribution of initial deviations to unemployment variation, which tends to zero as the length of time increases. β_ε is the percent of unemployment variation left unexplained.

To decompose the percentage variations in the gender unemployment gap, begin with the gender unemployment gap as

$$ln(u_t)^{Gap} = ln(u_t^M) - ln(u_t^F). \tag{9}$$

The deviations in the unemployment gap can, therefore, be written as

$$\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F). \tag{10}$$

This gap reads, to a close approximation, the percentage change in the male unemployment rate minus the percentage change in the female unemployment rate. It is a simple extension to decompose the unemployment gap using the above methodology. For example, the percentage contributions of differences in the proportionate variations in the ins, the inflow gap, to fluctuations in the unemployment gap is calculated as

$$\beta_s^{Gap} = \frac{Cov(\Delta ln(u_t)^{Gap}, C_{s_t}^{Gap})}{Var(\Delta ln(u_t)^{Gap})}, \tag{11}$$

where $C_{s_t}^{Gap} = C_{s_t}^M - C_{s_t}^F$. It is worth noting that this decomposition of the unemployment gap pertains to differences in the percentage deviations in unemployment between genders. That is, if the male unemployment rate rose from 0.05 to 0.0505, and the female unemployment rate rose from 0.1 to 0.11, $\triangle ln(u_t)^{Gap} = 0$. The robustness analysis in Section 6, presents a decomposition and results for deviations in unemployment rates as opposed to logarithmic deviations in unemployment rates, and show that the results remain qualitatively similar. In the next section, we present the results of the decomposition for all eighteen countries over the last 4 decades or so.

4 Results

Table 3 shows the results for the decomposition of unemployment rate variation by gender and of the gender unemployment gap. For clarification on interpretation, for male unemployment in Australia, the results read: variations in the inflows contribute to 37% of unemployment variation, variations in the outflows contribute to 66% of unemployment variation, 0% of unemployment variation can be attributed to initial deviations from steady-state, and changes in the error contribute to -2% of the variations in the unemployment rate. In line with Elsby et al. (2013), the first observation is that countries in the OECD experience very different labour market dynamics. For example, concentrating on males, for Netherlands and Italy, the outs of unemployment drive 14% and 76% of unemployment variation, respectively. A complete understanding of unemployment dynamics across countries, therefore, requires that we pay close attention to both the unemployment outflow and the unemployment inflow.

We can see clear differences in how different countries' labour markets operate, but what about differences between genders within countries? The column β_s^M-β_s^F, shows the male relative to female contributions of the ins to unemployment variation.[8] For two thirds of the countries, variations in the ins of unemployment contribute more to male unemployment variation than to female unemployment variation. Two economies that clearly divert from this trend are Japan and Luxembourg - in the latter, the ins contribute to 31% and 89% of male and female unemployment variation, respectively. On average, the ins of unemployment contribute 6% more to male unemployment variation than to female unemployment variation. As an example of how different the picture can be between genders, for the UK, the inflow:outflow contribution split to unemployment variation for males and females, respectively, is 57:43 and 21:83. These are drastically different. For males, inflows and outflows are equally important, and for females, changes in the outflows drive the vast majority of unemployment dynamics. There is clear heterogeneity in the ins and outs of unemployment between genders and by country.

The main purpose of this paper is to understand which flows contribute more to the dynamics of the unemployment gap, to which we now turn. Again, the gap that we refer to here is, differences in the logarithmic deviations in the unemployment rates between males and females. To be clear on interpretation, β_f^{Gap} for Australia reads, variations in the the outflow gap (differences in the variations of the outflows between gender) contribute to 24% of the variations in the unemployment gap. Notice that, for all countries, the contribution of variations in the inflow gap is greater than 50%. In fact, more than 80% of dynamics of the unemployment gap is explained by variations in the inflow gap for 14 of the 18 countries.[9] This is a remarkable result. When trying to understand why male and female unemployment rates change disproportionately over the business cycle, one generally need only understand why the inflow is more volatile for one gender over the other. See accompanying tables in Section B of the Appendix for the underlying empirical contributions.

For some of the countries – Germany, Netherlands, Portugal, Sweden and the UK – the contributions of changes in the outflow gap are actually negative. How do we interpret this? What this says is, for these countries, if the contributions of the outflow gap was always zero, all else the same, then the unemployment gap would be more volatile. To put it another way, the dynamics of the outflow gap dampens variations in the unemployment gap for these countries.

[8] Notice that this would be the negative of the relative outflow measure when initial deviations from steady-state and the error play no role.

[9] The negative values associated with contributions of variations in the outflow gap, means that if the outs behaved identically for males and females, then the unemployment gap would be more volatile.

Focus on recessions

Given the period of data, containing several downturns in many of the countries, the results do not necessarily hold when looking at any single sub-period. Using the framework described in Section 3, we focus in on sub periods in the data, to see which of the flows contributed to any disproportionate changes in the unemployment rates for males and females during particular time periods.

Figure 3 shows graphical analysis of the 1990-1995 and 2007-2012 periods using the framework described in Section 3. The solid lines in Figure 3 show the change in the gender unemployment gap relative to 1990 and 2007 for each country. More precisely, the solid line shows, the percentage change in the unemployment rate for males minus the percentage change in the unemployment rate for females relative to 1990 and 2007. A reading of 20, for example, means that the percentage increase in the male unemployment rate was 20 pp larger than the percentage increase in the female unemployment rate. The long dashed line shows the contribution to the unemployment gap of variations of the inflow gap, or C_{st}, and the short dashed line shows the contribution to the unemployment gap of variations of the outflow gap, or C_{ft}. The two dashed lines should approximately sum to the solid line since the contributions of initial deviations and the errors are in general small.

Looking at the solid line in Figure 3, for the majority of countries, we can see that the unemployment rate rose proportionately more for males than for females during the 1991 recession and the Great Recession. There is clear heterogeneity in the strength of the rise by country, however. In Ireland and Spain, the percentage rise in the male unemployment rate was almost 60 pp larger for males than for females in the Great Recession. For Japan and France, however, the proportionate difference in the rise between males and females was relatively small in the Great Recession.

Moving to the contributions, the larger rise in the ins for males is the main explanation for the rise in the gender unemployment gap during the 1991 recession and the Great Recession for most countries. Interestingly, the contribution of the outs is often negative, as we saw in the previous subsection. This means that, if the outflows for males followed the same pattern as the outflows for females, all else the same, then the rise in the gender unemployment gap during the 1991 recession and Great Recession would have been larger.[10]

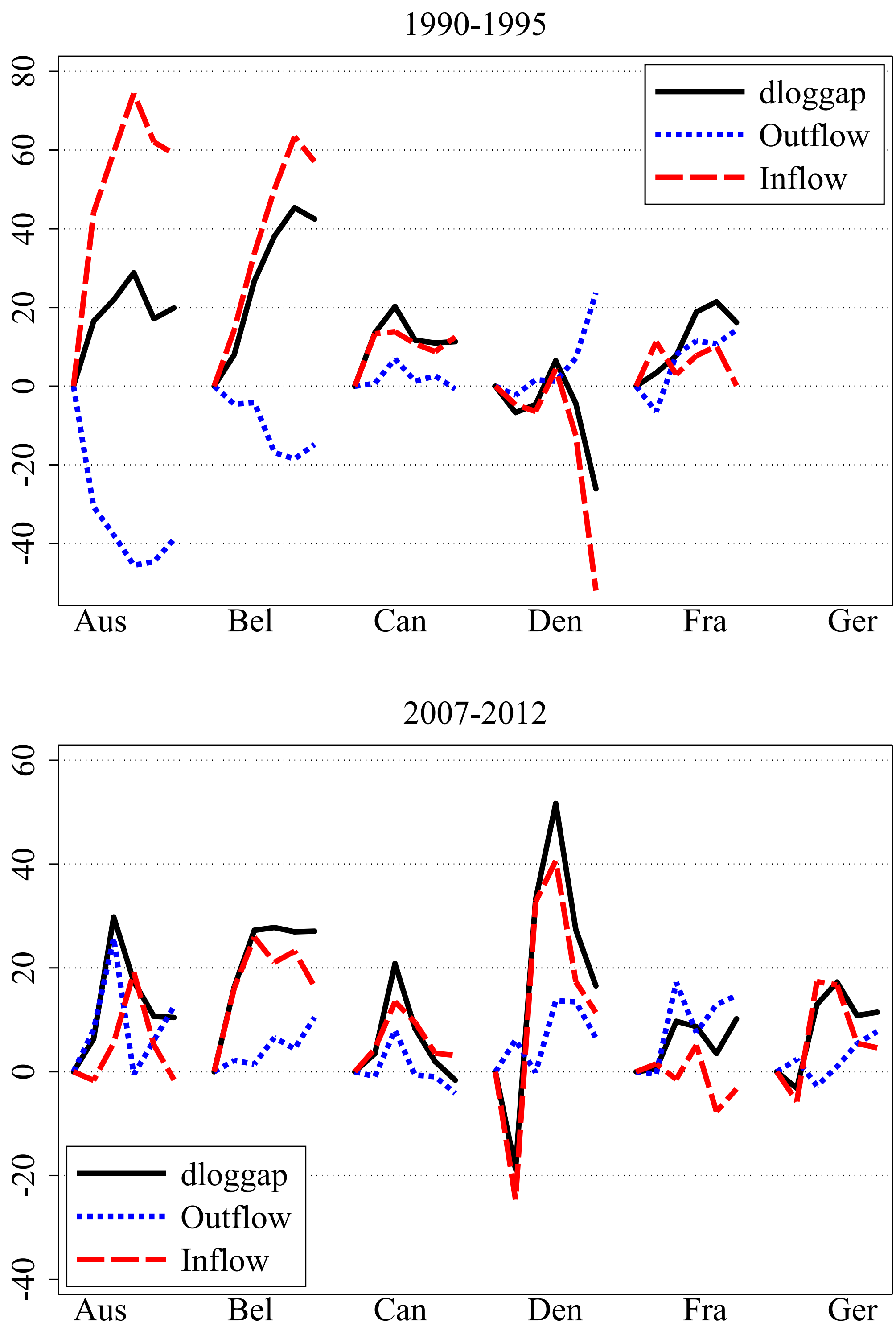
[10] These results square well with Hoynes (2012) who shows that the layoff rate rose more for males than for females during the Great Recession in the US.

TABLE 3: Contributions to unemployment variation for males, females and the gender unemployment gap

	Males				Females					Gap			
	β_f	β_s	β_0	β_ε	β_f	β_s	β_0	β_ε	β_s^M-β_s^F	β_f	β_s	β_0	β_ε
Australia	0.37	0.66	0.00	-0.02	0.53	0.48	0.00	-0.01	0.17	0.24	0.80	0.00	-0.04
Belgium	0.53	0.38	0.00	0.09	0.59	0.44	0.00	-0.03	-0.06	0.01	0.98	0.01	0.01
Canada	0.60	0.42	0.00	-0.01	0.66	0.34	0.00	-0.01	0.08	0.36	0.66	0.00	-0.02
Denmark	0.38	0.61	0.00	0.00	0.34	0.66	0.00	0.00	-0.06	-0.09	1.09	0.01	0.00
France	0.54	0.58	0.02	-0.14	0.36	0.69	0.02	-0.07	-0.11	0.50	0.58	0.01	-0.09
Germany	0.47	0.51	0.04	-0.02	0.84	0.12	0.06	-0.02	0.39	-0.58	1.62	-0.01	-0.03
Ireland	0.57	0.47	0.04	-0.10	0.67	0.35	0.03	-0.06	0.12	-0.02	1.05	0.02	-0.03
Italy	0.76	0.33	0.01	-0.10	1.01	0.11	0.02	-0.14	0.21	0.04	1.01	0.01	-0.05
Japan	0.51	0.48	0.00	0.01	0.30	0.70	0.00	0.00	-0.22	-0.11	1.11	0.00	0.00
Luxembourg	0.69	0.31	0.01	-0.01	0.11	0.89	0.00	-0.02	-0.59	0.05	0.90	0.04	0.03
Netherlands	0.14	0.78	0.06	-0.01	0.42	0.62	0.00	-0.01	0.16	-0.20	0.99	0.05	0.07
New Zealand	0.49	0.57	0.05	-0.11	0.52	0.51	0.02	-0.05	0.06	0.16	0.73	0.02	0.10
Norway	0.39	0.60	0.00	0.00	0.41	0.58	0.00	0.00	0.02	-0.12	1.13	0.00	0.00
Portugal	0.41	0.59	0.00	0.00	0.55	0.44	0.01	0.00	0.15	-0.32	1.32	-0.01	0.01
Spain	0.57	0.51	0.00	-0.08	0.84	0.17	0.00	-0.02	0.33	0.23	0.87	0.00	-0.10
Sweden	0.26	0.73	0.00	0.00	0.22	0.76	0.00	0.03	-0.02	-0.21	1.23	0.00	0.00
United Kingdom	0.43	0.57	0.00	0.00	0.83	0.21	0.00	-0.04	0.37	-0.24	1.19	0.01	0.03
United States	0.67	0.34	0.00	-0.02	0.79	0.22	0.00	-0.01	0.12	0.37	0.64	0.00	-0.02
Average	0.49	0.52	0.01	-0.03	0.56	0.46	0.01	-0.03	0.06	0.00	0.99	0.01	-0.01

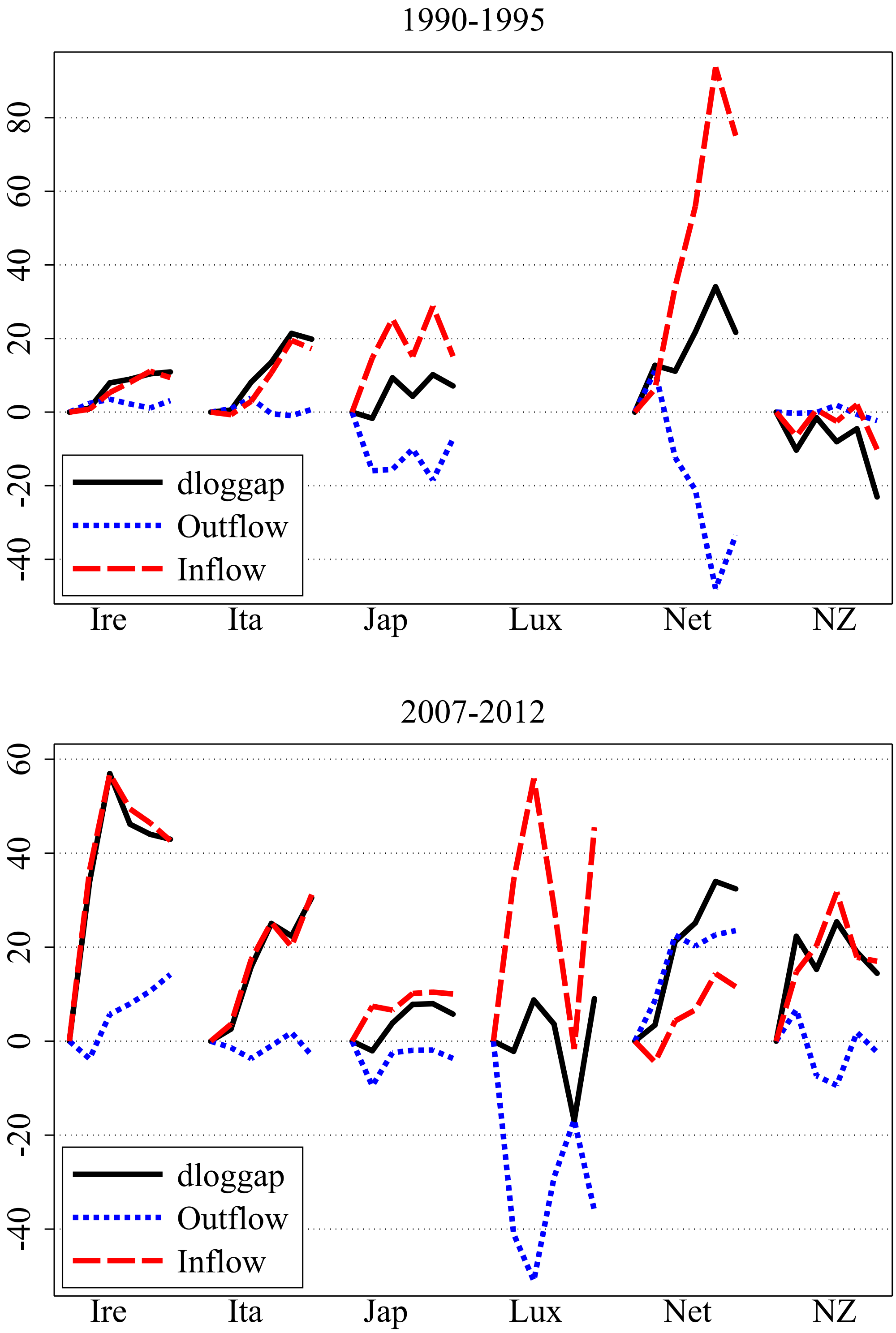
Note: Gender unemployment gap is defined as $\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F)$. The interpretation of the Male results for Australia read: Variations in the outflows contribute to 37% of unemployment variation, variations in the inflows contribute to 66% of unemployment variation, 0% of unemployment variation can be attributed to initial deviations from steady-state, and changes in the error contribute to -2% of the variations in the unemployment rate. Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

FIGURE 3: The contributions of changes in the unemployment flows to changes in the unemployment gap during the 1990-1995 and 2007-2012 periods



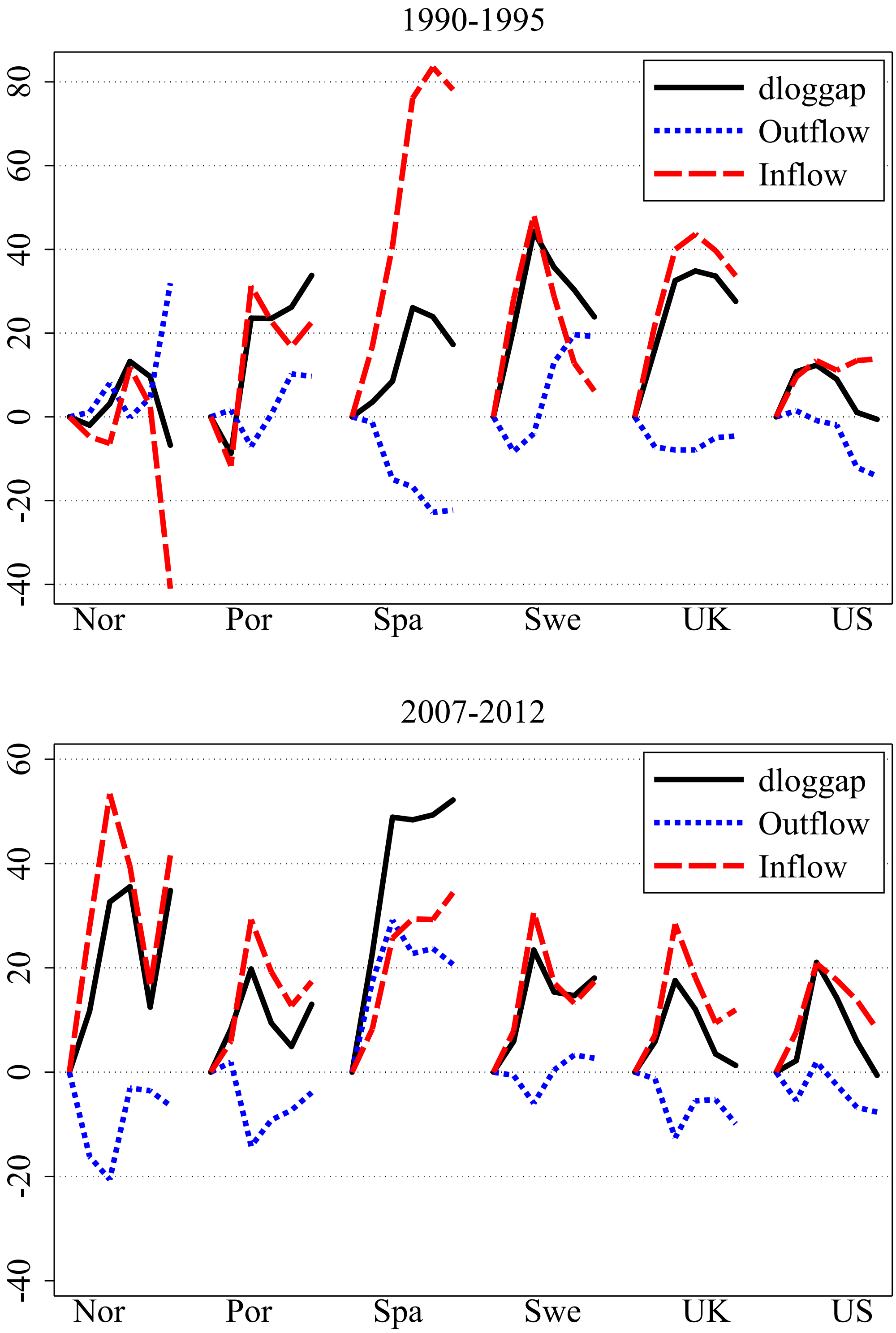
Note: The bold line represents the cumulative change in the unemployment gap, $\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F)$, relative to 1990 (top) and 2007 (bottom). The long dashed line shows the contributions of changes in the inflow gap to changes in the cumulative unemployment gap. The short dashed line shows the contributions of changes in the outflow gap to changes in the unemployment gap.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

FIGURE 3: The contributions of changes in the unemployment flows to changes in the unemployment gap during the 1990-1995 and 2007-2012 periods (cont'd)



Note: The bold line represents the cumulative change in the unemployment gap, $\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F)$, relative to 1990 (top) and 2007 (bottom). The long dashed line shows the contributions of changes in the inflow gap to changes in the cumulative unemployment gap. The short dashed line shows the contributions of changes in the outflow gap to changes in the unemployment gap.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

FIGURE 3: The contributions of changes in the unemployment flows to changes in the unemployment gap during the 1990-1995 and 2007-2012 periods (cont'd)



Note: The bold line represents the cumulative change in the unemployment gap, $\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F)$, relative to 1990 (top) and 2007 (bottom). The long dashed line shows the contributions of changes in the inflow gap to changes in the cumulative unemployment gap. The short dashed line shows the contributions of changes in the outflow gap to changes in the unemployment gap.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

5 Towards understanding the underlying mechanism

We have shown that the cyclical changes in the gender unemployment gap appear to be predominantly, in a lot of cases entirely, explained by the differing volatility of flows *into* unemployment. What is the underlying explanation for this result? In this section we document a key consistent stylised fact across all countries: There is a positive relationship between the share of males in a sector, and the correlation of that sectors output with aggregate output.

In the US Albanesi and Sahin (2018) show that if you assign the male industry composition to the female labour force, then the rise in the gender unemployment gap during recessions would fall by about a half. That is, in the past males have tended to be in jobs that are more susceptible to economic swings than females. This suggests that output in male dominated sectors shows more cyclicality than output in female dominated sectors. To assess whether this is true for all countries, we compile data from the OECD on male-female sector shares, a time series of output in those sectors, and output in the aggregate.[11]

We detrend the output data using a Hodrick Prescott filter on quarterly data. We then correlate the cyclical components of sector and aggregate output, and plot these against the percentage of males by sector. Figures 4 and 5 show the results of this exercise, where, in the case of 5, we have grouped all Continental European countries into one figure, and Anglo Saxon countries and South Korea into another. We find a clear positive relationship between these two measures. A regression of the correlation of sector output with overall output on the male sector share with country fixed effects, reveals a coefficient of 0.69 with a standard error of 0.11 - a 1 percentage point increase in the share of males in a sector is associated with a 0.69 percentage point increase in the correlation of a sectors output with overall output.

Figure 6 shows the the figure for the UK and US, with the points representing the sectors named. Again, we see a clear positive association between the two measures.[12] Output in male dominated sectors, such as Construction and Manufacturing, show a strong correlation with aggregate output. Whereas output in female dominated sectors, such as health care and education, show a weaker correlation with aggregate output over the cycle.

At first glance, this looks like a public sector story: across the 18 countries in our sample, the female share in Public Administration, Health or Education sectors is 66 per cent. Whilst selection into public jobs is part of the explanation, it does not explain everything. For example, if we *exclude* the public sector from our sample, the coefficient in the above regression falls to 0.41 (p-value = 0.003), but remains both economically large

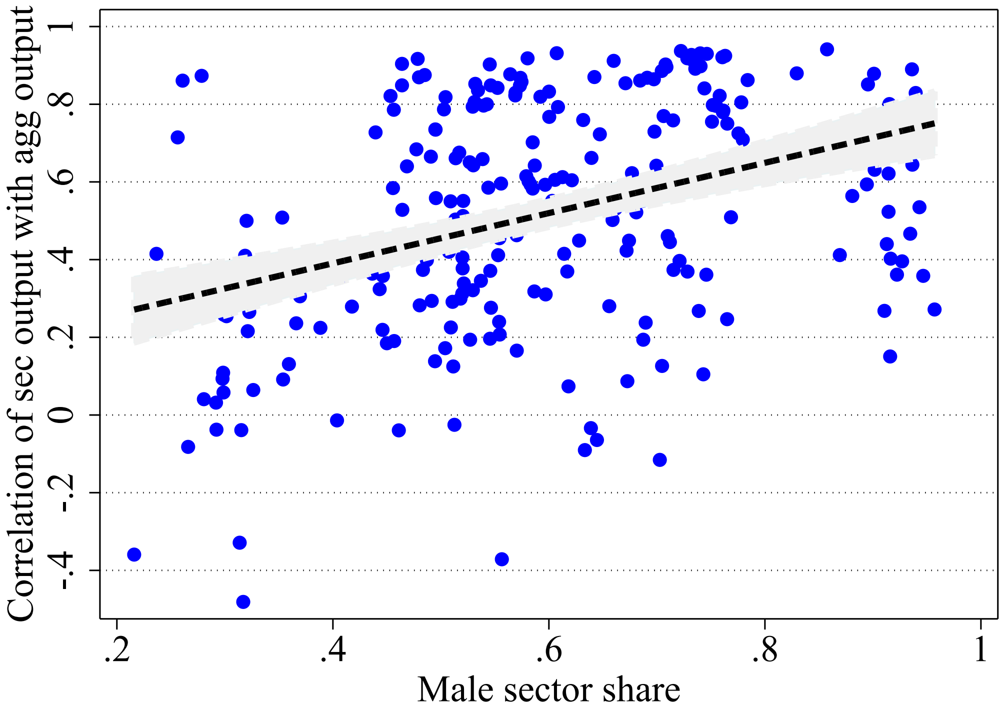
[11] Sectors that we adopt in the OECD data are, Agriculture, forestry and fishing; Industry; Manufacturing; Construction; Distribution, trade, accommodation and food services; IT and communications; Finance and insurance; Real estate; Scientific and administration; Public admin, health and education.

[12] In the Appendix, we show a clear positive association for almost all countries included in Figure 5.

and statistically significant. The same is true of individual countries. For example, excluding health and education from the Canadian data reduces the correlation between output cyclicality and the male share from 0.74 to 0.54. For the US, the removing the same sectors reduces the correlation from 0.72 to 0.36.

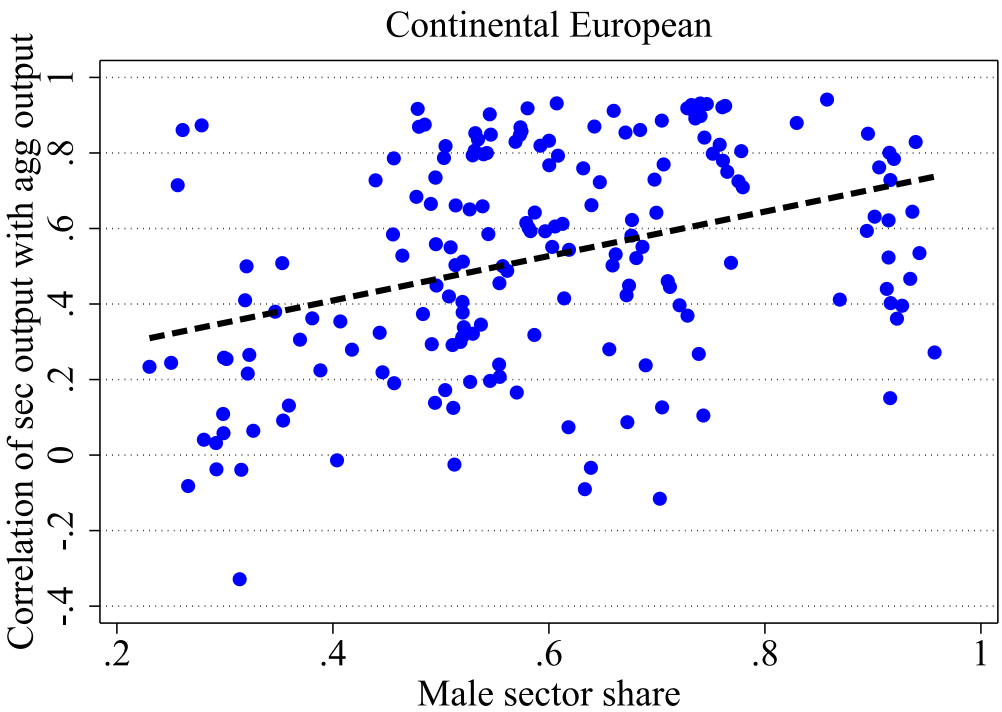
These observations suggests an underlying story for the results on the gender unemployment gap for all countries that are documented in this paper, and reaffirms the sector story made by Albanesi and Sahin (2018) in the US: males are hired into sectors that are more susceptible to economic swings, which in turn means the average precarity of male jobs falls more in recessions relative to females.

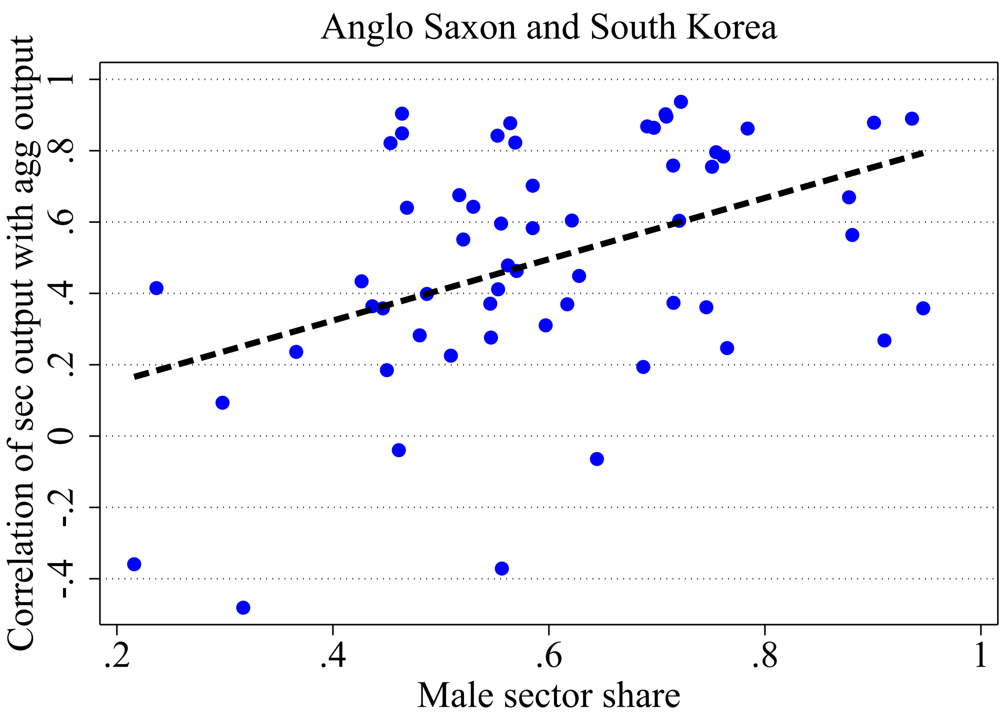
FIGURE 4: Relationship between male share and the correlation of sector output with overall output – all countries



Note: Countries included are Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Latvia, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom and United States. Excluded Agricultural sector.

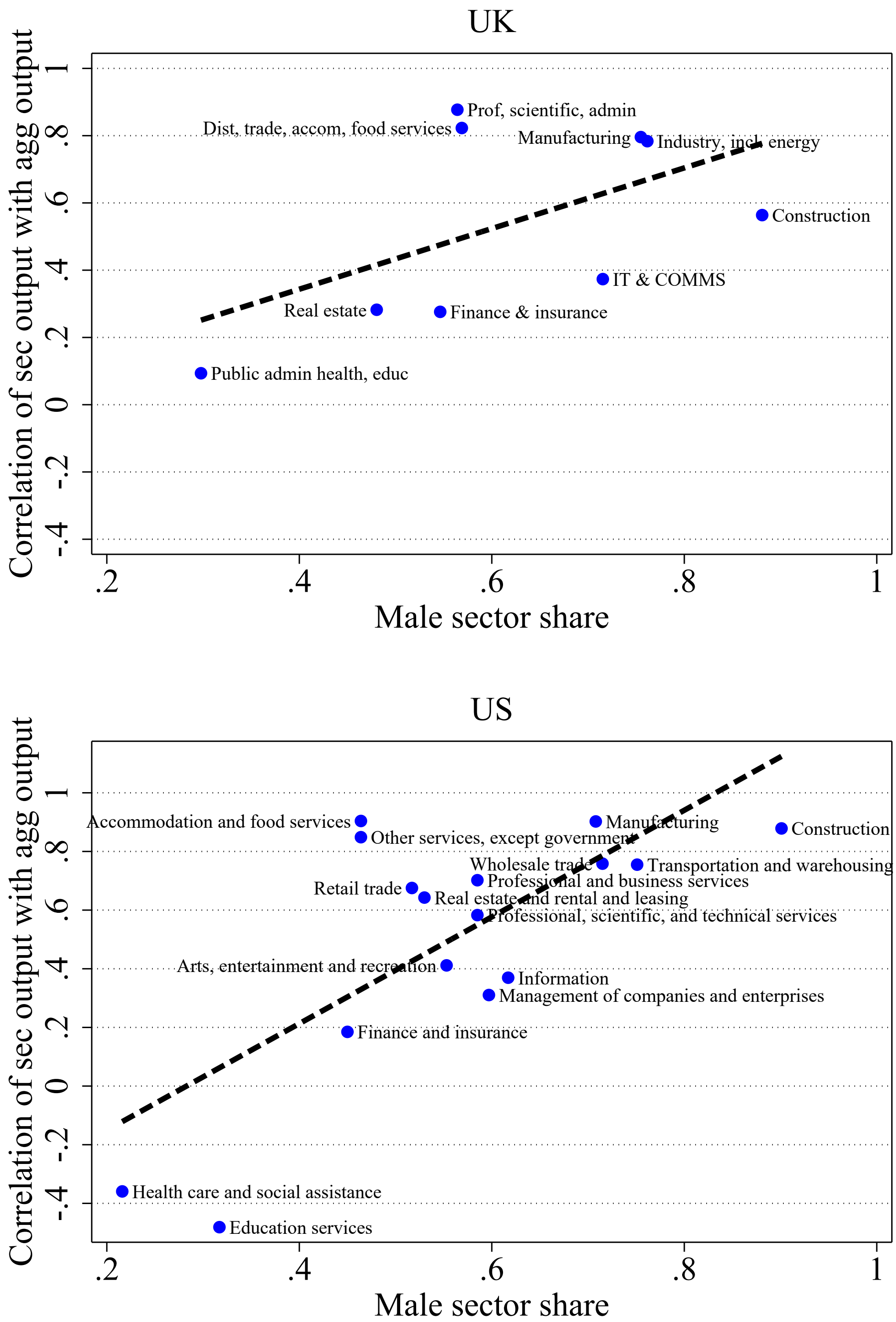
FIGURE 5: Relationship between male share and the correlation of sector output with overall output for Continental European (top), and Anglo Saxon and South Korea (bottom)





Note: Countries included in the top figure are Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain and Sweden. Countries included in the bottom figure are Canada, Ireland, Japan, United Kingdom and United States. Excluded Agricultural sector.

FIGURE 6: Relationship between male share and the correlation of sector output with overall output for UK (top), and US (bottom)



Note: Excluded Agricultural sector.

6 Further discussion and robustness

The preceding sections have demonstrated that the differing cyclicality of the inflow between males and females is the main explanation for the dynamics of the unemployment gap, and that one of the underlying explanations for this is the male-female composition by sector. In this section, we discuss whether any simplifications from the analysis may affect these results.

Logarithmic vs levels decomposition

The baseline decomposition is one of differences in logarithmic deviations in the unemployment rates by sex. What if we were instead interested in differences in deviations in the unemployment rates by sex. We can assess whether an analysis of levels results in any clear differences using a slight modification of the decomposition in Section 3. We begin with 3, which we write down again as:

$$u_t = \left(1 - e^{-12(s_t+f_t)}\right)u_t^* + e^{-12(s_t+f_t)}u_{t-12}. \tag{12}$$

Realising that $e^{-12(s_t+f_t)} \approx e^{-12(s_{t-1}+f_{t-1})}$, and first differencing (12), we can write down changes in unemployment as

$$\Delta u_t = (1 - e^{-12(s_t+f_t)})\Delta u_t^* + e^{-12(s_t+f_t)}\Delta u_{t-12} + \varepsilon_t. \tag{13}$$

As with the logarithmic decomposition, changes are equal to a distributed lag of changes in the steady state level of unemployment, and also an initial condition. It is now straight forward to decompose variations in levels gender unemployment gap into the contributions due to changes in the inflow gap and outflow gap since

$$\Delta u_t^M - \Delta u_t^F = u_t^{Gap} - u_{t-t}^{Gap} = \Delta u_t^{Gap}, \tag{14}$$

where $u_t^{Gap} = u_t^M - u_t^F$.[13] Table A1 shows the results using this decomposition compared with the logarithmic decomposition described in Section 3. The results are very similar.

The participation margin

Elsby et al. (2015) shows that transitions at the participation margin are important for labour market fluctuations. In Section 2, the main piece of information used to estimate the unemployment flows is unemployment by duration, in particular the percent of the labour force who have been unemployed for less than one month. As described previously, this stock contains workers who have just left their job and moved into unemployment, but also workers who have just entered the labour force and moved into unemployment. As shown previously, taking into account flows into and out of the labour force, we can write

[13] We provide further mathematical details in the online Appendix.

the steady state unemployment rate as

$$u_t^* = \frac{s_t}{s_t + f_t} \equiv \frac{\lambda_t^{eu} + \frac{\lambda_t^{en}\lambda_t^{nu}}{\lambda_t^{ne}+\lambda_t^{nu}}}{\lambda_t^{eu} + \frac{\lambda_t^{en}\lambda_t^{nu}}{\lambda_t^{ne}+\lambda_t^{nu}} + \lambda_t^{ue} + \frac{\lambda_t^{un}\lambda_t^{ne}}{\lambda_t^{ne}+\lambda_t^{nu}}}, \tag{15}$$

where λ_t^{ij} represents the monthly transition probability from state i to state j at time t, and e and n refer to employment and inactivity rates at time t. The unemployment inflow and outflow rates are, respectively, inflated by the two terms, $\lambda_t^{enu} = \frac{\lambda_t^{en}\lambda_t^{nu}}{\lambda_t^{ne}+\lambda_t^{nu}}$ and $\lambda_t^{une} = \frac{\lambda_t^{un}\lambda_t^{ne}}{\lambda_t^{ne}+\lambda_t^{nu}}$. Following Smith (2012), we will interpret these flows as transitions from employment to unemployment via inactivity, and unemployment to employment via inactivity, respectively. It is possible that some of the contributions of the inflows to the dynamics of the unemployment gap, should be attributed to variations of transitions through inactivity.

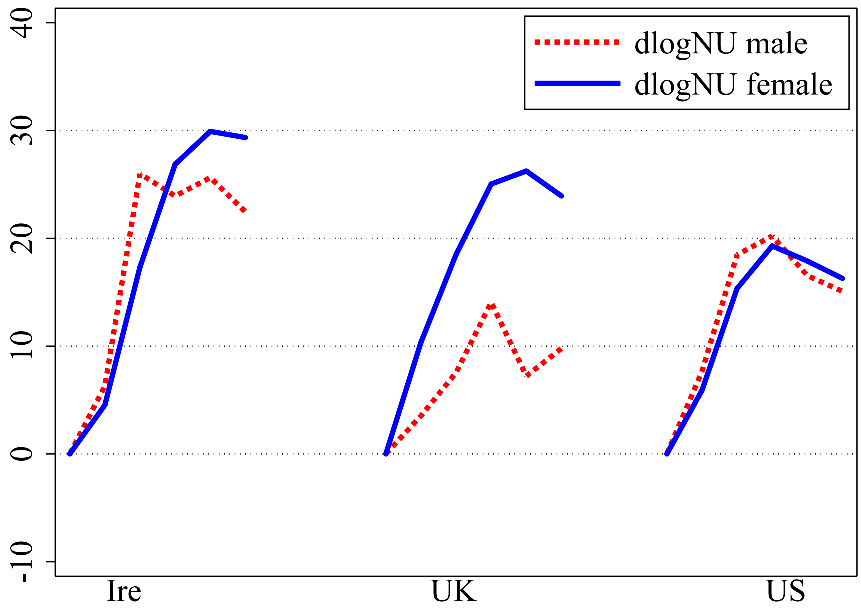
Flows into unemployment from inactivity would have to show larger increases for males over females during recessions. The reality of the added worker effect would suggest the opposite (see recent work on the added worker effect in Mankart and Oikonomou (2016)) - females are more likely to enter unemployment from inactivity during recessions to mitigate the consequences of spousal job loss. This would mean that the contribution of employment to unemployment transitions is actually downward biased.

We collect micro data from Ireland, the UK and the US, in order to construct the transition rates from inactivity to unemployment. Figure 7 shows the log changes in the inactivity to unemployment transition probability from 2007 - 2012, relative to 2007, for each country. If the dynamics of the unemployment gap are driven by differences in variations of the inactivity to unemployment transitions between genders as opposed to employment to unemployment transitions, we would expect to find larger percentage increases in inactivity to unemployment transitions for males over females. There is no clear evidence of this for this sub-sample of countries. In fact, for the UK the rise is far larger for females than males.

Time aggregation

Using the OECD data, we are only able to estimate flows at a yearly frequency, a relatively low frequency. Estimating flows with low frequency data may create issues of time aggregation - one may miss many transitions between survey dates. Shimer (2012) shows, however, that the technique used for estimating the inflow in this paper corrects for this bias. It is possible, however, that the outflow measure misses some exits from unemployment. This is likely to be negligible for two reasons. First, any biases will be significant if inflows back into unemployment are large. As we have seen in Table 2, the inflows are very small and so the number of outflows that are missed is likely small. Second, because we are focusing on differences between genders, any small biases will affect both

FIGURE 7: The percentage change in the inactivity to unemployment probability between 2007-2012, relative to 2007



Source: Data compiled from the Irish LFS and UK LFS, author calculations. US data taken from BLS (2018).

males and females in a similar way. It is likely, therefore, that the impact of time aggregation is very small.

Cross country comparison

Because of the difference in available data, some countries in the sample have longer periods, and some short. Unemployment flows for the US can be estimated for 5 decades, and unemployment flows for New Zealand can only be estimated for just over 3 decades. It is of interest to see if the results are similar when looking at a more recent period that is common to all, for example 2000-2018.[14] Table A2 shows the results for the entire period and the 2000-2018 period accompanied with the ratio of unemployment flows between males and females. First, focusing on the unemployment flows, the difference in the size of the inflows has reduced in recent times on average suggesting a convergence in the trend of males and female outcomes in recent times (Albanesi and Sahin (2018)). The contributions to changes in the unemployment gap, however, are very similar. The results described in Section 4 are not driven by any one sub-period in the data and seem to persist even when the average inflows between males and females converge.

[14]The OECD has gone to great lengths to harmonise the statistics, precisely so cross-country comparisons can be made. In particular, for unemployment, the OECD have created a blanket criteria to assign a survey participant as unemployed, precisely the information used in this paper.

The COVID-19 recession: this time it's different?

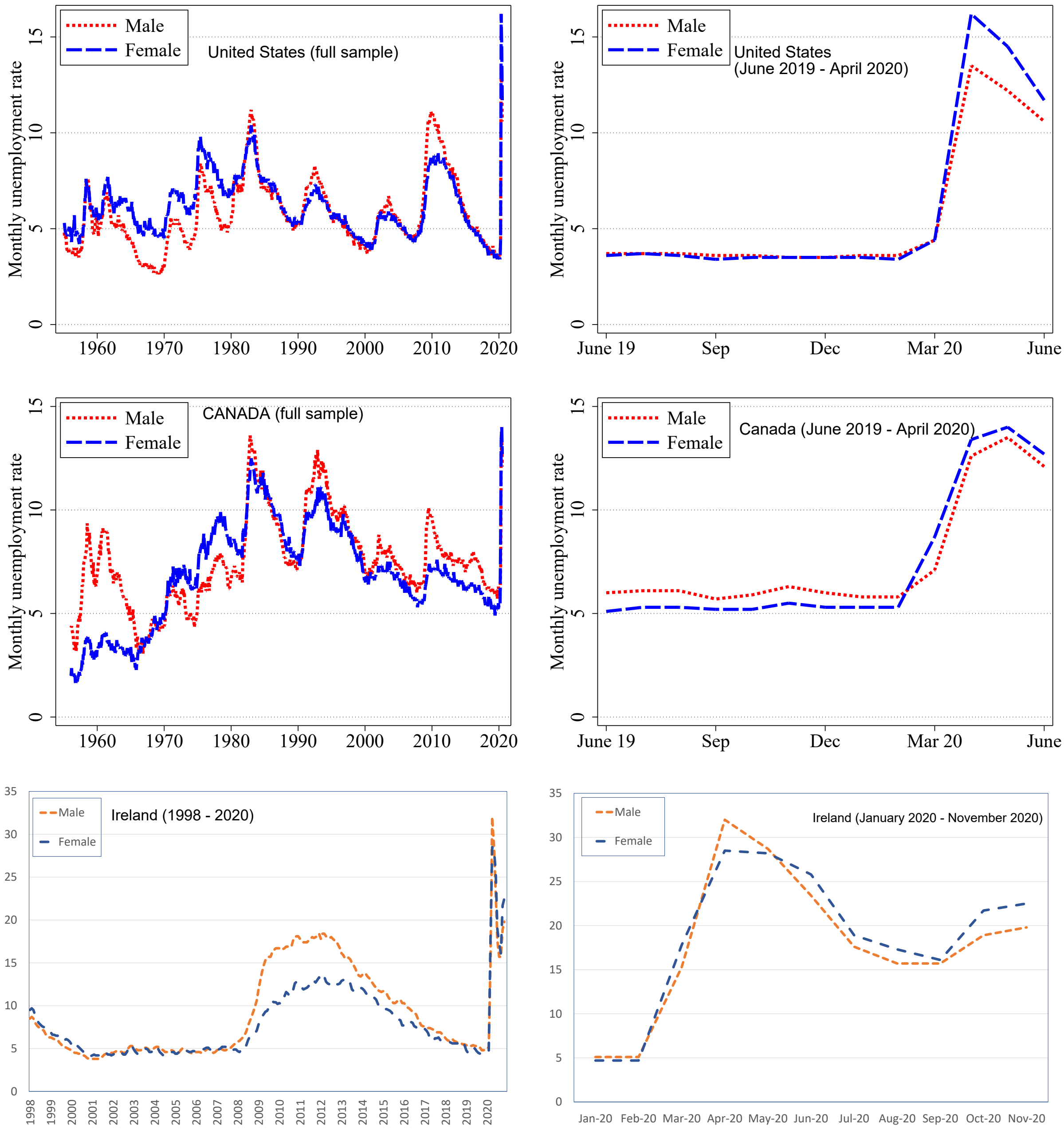
The COVID-19 recession has resulted in a large negative labour demand shock, as governments attempt to limit the spread of the virus through various social distancing policies and restrictions on economic activity. The restrictions have impacted sectors and jobs that typically require more face-to-face interaction, like services. This has prompted some to call the COVID-19 shock a 'services-led recession'.[15]

Figure 8 shows the unemployment rate by gender for the US and Canada (where the last date is April 2020) and Ireland (to November 2020). The rise in unemployment during the current crisis dwarfs the unemployment rise in any economic downturn over the entirety of available data from the OECD.

We have already showed that, for the period analysed in this paper, the unemployment rate tends to rise proportionately more for males than females in recessions, and that this driven by larger *inflows* into unemployment for males. This trend seems to have reversed during the 2020 crisis, with the female unemployment rate rising significantly more than for males. Although, as the data for Ireland shows, timing matters. Earlier restrictions, which inclued male dominated sectors like construction and industry were initially shut down; whereas later restrictions focused solely on female dominated services sectors. If the results in the current paper extend to the 2020 crisis, then the reason for the larger rise in female unemployment is predominantly due to a proportionately larger rise in females separating from their jobs and flowing into unemployment, and the types of industries that are being affected in the current crisis are different to those affected in crises over the past four decades, which are more likely to employ women over men.

[15] See for example Christine Lagarde's speech at the November 2020 *ECB Forum on Central Banking*.

FIGURE 8: The monthly unemployment rate by gender in the US (top), Canada (Middle) and Ireland (bottom)



Source: Data compiled from OECD (2018a) and CSO (Ireland, Tables MUM01 and MUM02, excluding workers on short-time, subsidised or temporary furlough.

7 Conclusion

This paper has assessed why the variance of unemployment is so markedly different between genders in many labour markets. The disparity is due to either, differences in the variations of flows into unemployment, or differences in variations of flows out of unemployment. Using publicly available harmonised data from 18 OECD countries over the last 4 decades or so, we have shown that the variations in the gender unemployment gap are mostly due to differences in the variations of the inflows for males relative to females. In fact, more than 80% of dynamics of the unemployment gap is explained by differences in the variations of the ins for 14 of the 18 countries. Using data on output by sector and male sector share, we have also found that sectors that employ more males, seem to more susceptible to economic swings. Which is a consistent result across all countries.

These results paint a clear and simple picture behind the dynamics of the gender unemployment gap across countries in the OECD. Males tend to sort into sectors where output declines more in recessions. This in turn increases the average precarity of a male's job more than for a female. Which increases unemployment inflows more for males then for females.

Sectoral composition, however, is undoubtedly not the only explanation behind why males tend to experience greater increases in inflows during recessions. Avenues for future work should be to uncover further asymmetric features behind male and female unemployment inflow dynamics.

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Appendix A. More tables

TABLE A1: Comparison between the non-logarithmic and logarithmic deviations in the unemployment gap

	Non-logarithmic gap				Logarithmic gap			
	β_f	β_s	β_0	β_ε	β_f	β_s	β_0	β_ε
Australia	-0.01	1.03	0.00	-0.02	0.24	0.80	0.00	-0.04
Belgium	-0.03	1.02	0.00	0.01	0.01	0.98	0.01	0.01
Canada	0.43	0.58	0.00	0.00	0.36	0.66	0.00	-0.02
Denmark	-0.07	1.09	0.01	-0.03	-0.09	1.09	0.01	0.00
France	0.44	0.54	0.01	0.01	0.50	0.58	0.01	-0.09
Germany	-0.15	1.23	-0.02	-0.06	-0.58	1.62	-0.01	-0.03
Ireland	0.42	0.73	0.00	-0.15	-0.02	1.05	0.02	-0.03
Italy	0.07	0.92	0.05	-0.03	0.04	1.01	0.01	-0.05
Japan	-0.12	1.12	0.00	0.00	-0.11	1.11	0.00	0.00
Luxembourg	0.08	0.99	0.00	-0.07	0.05	0.90	0.04	0.03
Netherlands	0.20	0.96	-0.01	-0.15	-0.20	0.99	0.05	0.07
New Zealand	0.09	0.98	0.01	-0.07	0.16	0.73	0.02	0.10
Norway	-0.23	1.22	0.00	0.01	-0.12	1.13	0.00	0.00
Portugal	-0.11	1.03	0.00	0.07	-0.32	1.32	-0.01	0.01
Spain	0.58	0.37	0.24	-0.19	0.23	0.87	0.00	-0.10
Sweden	0.23	0.82	0.00	-0.05	-0.21	1.23	0.00	0.00
United Kingdom	-0.28	1.28	0.02	-0.01	-0.24	1.19	0.01	0.03
United States	0.49	0.52	0.00	0.00	0.37	0.64	0.00	-0.02
Average	0.11	0.91	0.02	-0.04	0.00	0.99	0.01	-0.01

Note: The non-logarithmic unemployment gap refers to $\Delta u_t^{Gap} = \Delta u_t^M - \Delta u_t^F$, and the contributions are estimated using (13). The logarithmic unemployment gap refers to $\Delta ln(u_t)^{Gap} = \Delta ln(u_t^M) - \Delta ln(u_t^F)$, and the contributions are estimated using (7). The interpretation of the non-logarithmic results for Australia are: Differences in the variations in the outflows between males and females contribute to -1% of the dynamics of the unemployment gap, differences in the variations in the inflows between males and females contribute to 1.03% of the dynamics of the unemployment gap, 0% of the dynamics of the unemployment gap can be attributed to differences in initial deviations from steady-state between males and females, and changes in the error contribute to -2% of the dynamics of the unemployment gap.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

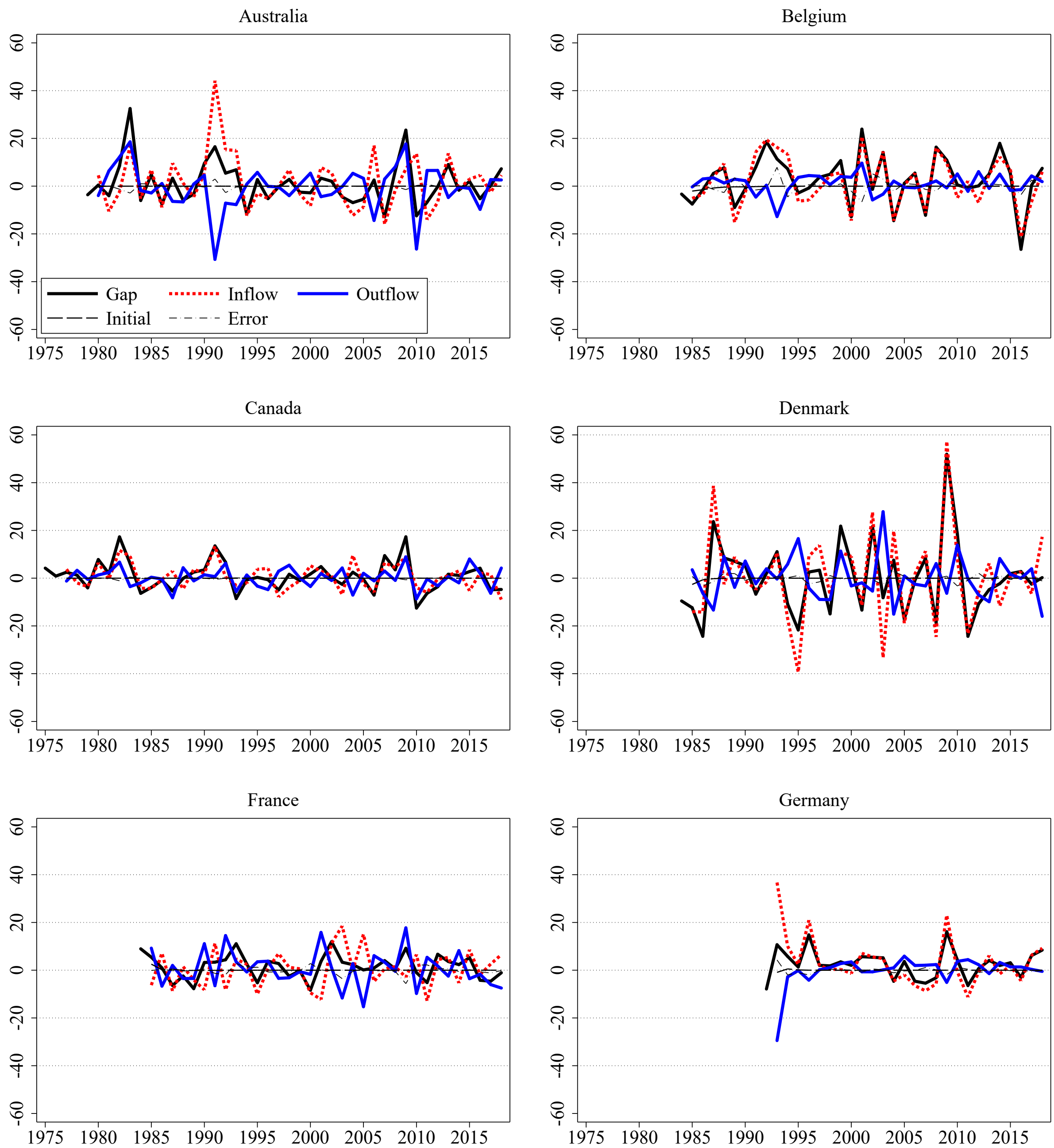
TABLE A2: Contributions to the dynamics of the unemployment gap for different periods and the relative inflows and outflows

	Entire period						2000-2018					
			Gap						Gap			
	$\frac{s^M}{s^F}$	$\frac{f^M}{f^F}$	β_f	β_s	β_0	β_ε	$\frac{s^M}{s^F}$	$\frac{f^M}{f^F}$	β_f	β_s	β_0	β_ε
Australia	0.89	0.93	0.24	0.80	0.00	-0.04	1.02	1.04	0.48	0.55	0.00	-0.03
Belgium	0.79	1.10	0.01	0.98	0.01	0.01	0.93	0.99	0.08	0.90	0.00	0.02
Canada	0.93	0.88	0.36	0.66	0.00	-0.02	1.02	0.88	0.42	0.60	0.00	-0.01
Denmark	0.87	1.03	-0.09	1.09	0.01	0.00	0.90	0.99	-0.11	1.11	0.00	0.00
France	0.85	1.10	0.50	0.58	0.01	-0.09	0.96	1.04	0.56	0.62	0.00	-0.18
Germany	1.01	1.05	-0.58	1.62	-0.01	-0.03	1.09	0.98	-0.28	1.33	0.00	-0.06
Ireland	0.69	0.63	-0.02	1.05	0.02	-0.03	0.75	0.63	-0.05	1.06	0.02	-0.03
Italy	0.65	1.10	0.04	1.01	0.01	-0.05	0.75	1.07	-0.16	1.07	0.00	0.09
Japan	0.68	0.67	-0.11	1.11	0.00	0.00	0.67	0.60	-0.26	1.33	0.00	-0.07
Luxembourg	0.64	0.91	0.05	0.90	0.04	0.03	0.66	0.88	0.14	0.92	0.00	-0.06
Netherlands	0.70	1.04	-0.20	0.99	0.05	0.07	0.80	0.94	0.08	0.65	0.05	0.10
New Zealand	0.87	0.84	0.16	0.73	0.02	0.10	0.82	0.88	0.22	0.70	0.00	0.08
Norway	1.03	0.90	-0.12	1.13	0.00	0.00	1.02	0.87	0.00	1.00	0.00	0.00
Portugal	0.96	1.15	-0.32	1.32	-0.01	0.01	0.95	0.99	-0.36	1.26	0.00	0.11
Spain	0.84	1.28	0.23	0.87	0.00	-0.10	0.85	1.18	0.48	0.57	0.00	-0.05
Sweden	0.99	0.95	-0.21	1.23	0.00	0.00	0.93	0.89	-0.24	1.24	-0.01	-0.02
United Kingdom	0.90	0.72	-0.24	1.19	0.01	0.03	0.89	0.76	-0.42	1.36	0.00	0.06
United States	0.77	0.83	0.37	0.64	0.00	-0.02	1.03	0.96	0.32	0.72	0.00	-0.04
Average	0.84	0.95	0.00	0.99	0.01	-0.01	0.89	0.92	0.05	0.94	0.00	-0.01

Note: The interpretation of the Male results for Australia read: Differences in the proportionate variations in the outflows between males and females contribute to 24% of the dynamics of the unemployment gap, differences in the proportionate variations in the inflows between males and females contribute to 80% of the dynamics of the unemployment gap, 0% of the dynamics of the unemployment gap can be attributed to differences in initial deviations from steady-state between males and females, and changes in the error contribute to -4% of the dynamics of the unemployment gap.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

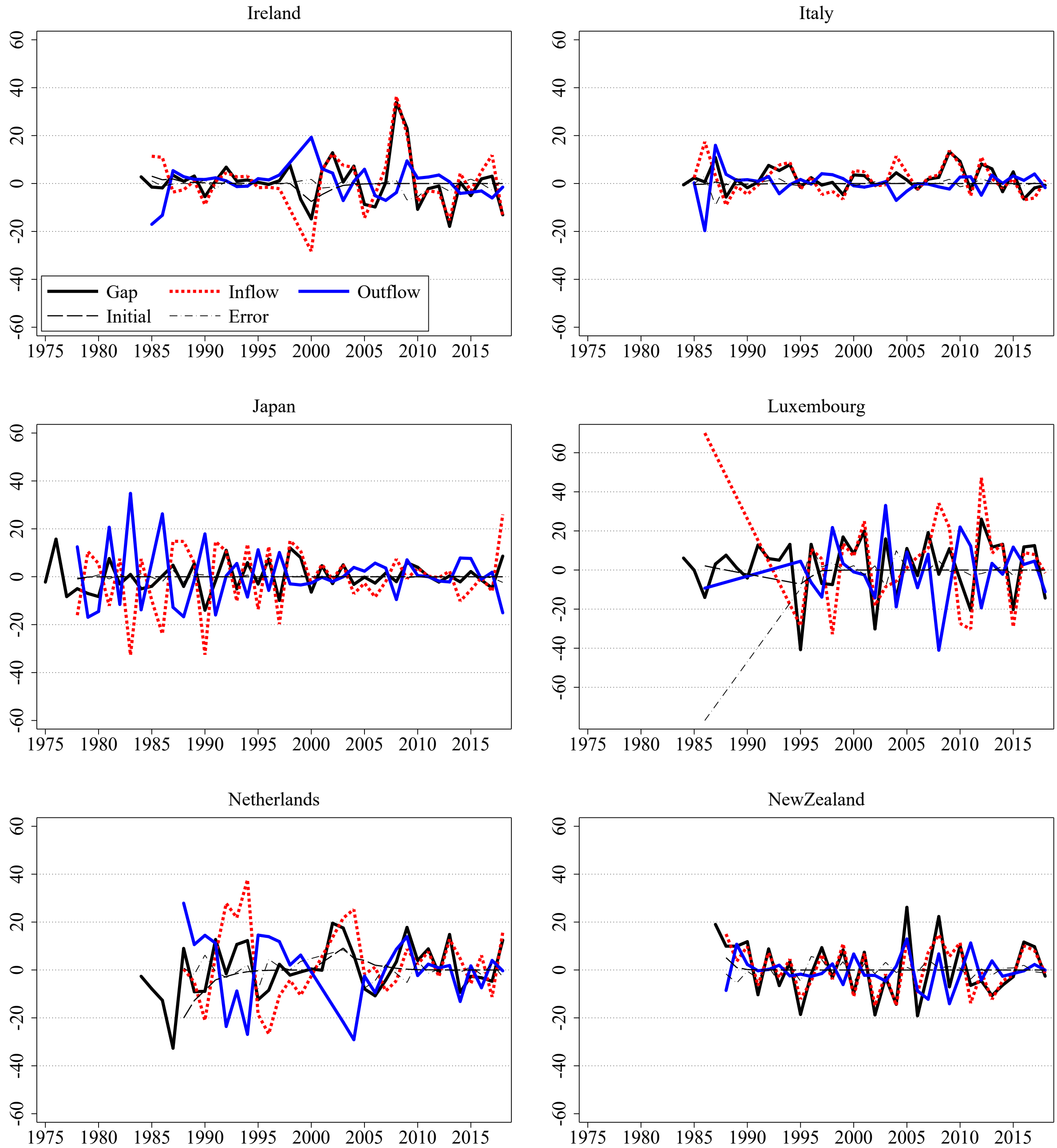
Appendix B. More figures

FIGURE B1: The contributions of the unemployment flows to the unemployment gap



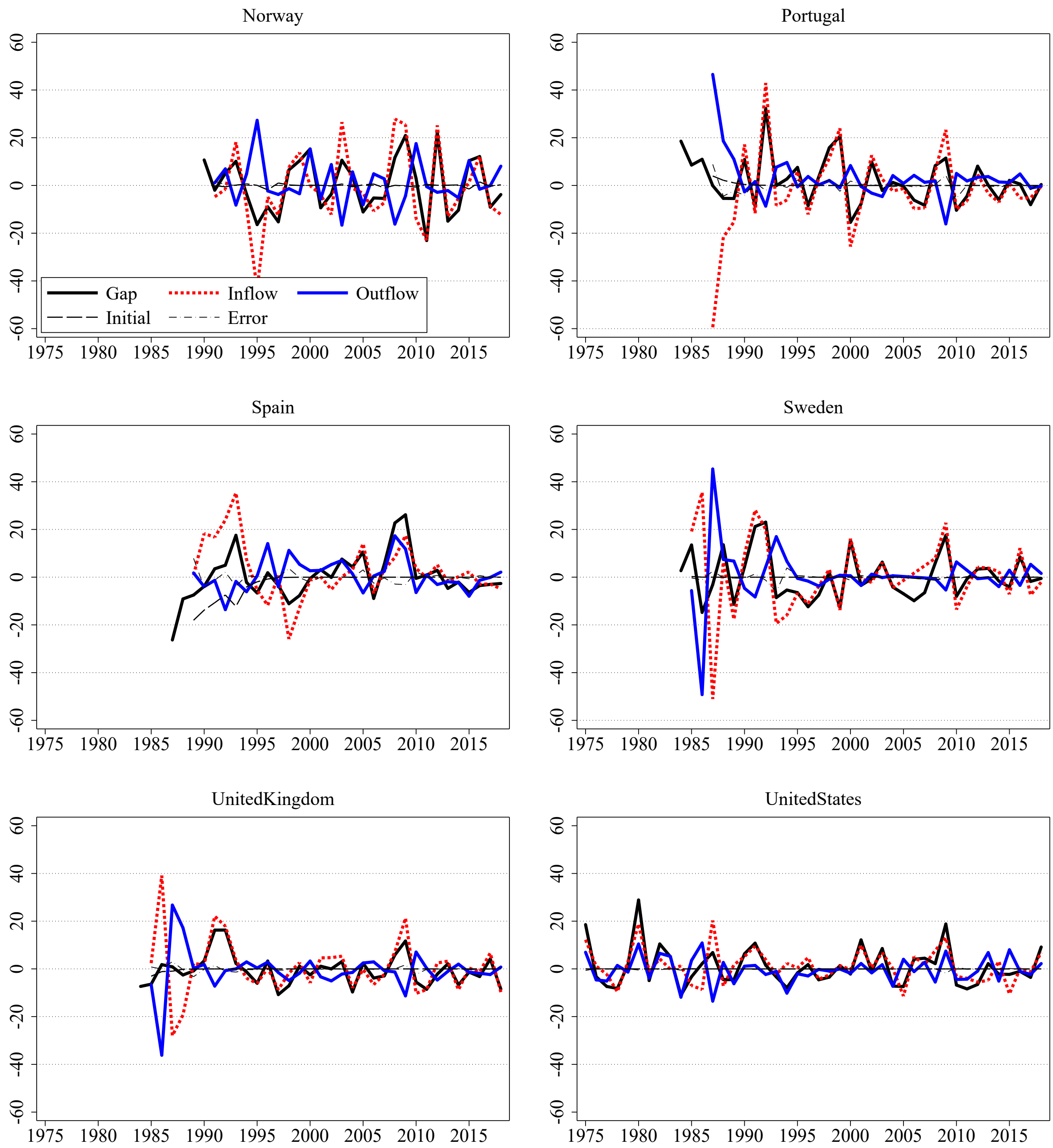
Note: The bold line represents the percentage change in unemployment for males minus the percentage change in unemployment for females. The long dashed line shows the contributions to the increase in the bold line of differences in changes in the ins between males and females. The short dashed line shows the contributions to the increase in the bold line of differences in changes in the outs between males and females. Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

FIGURE B1: The contributions of the unemployment flows to the unemployment gap (cont'd)



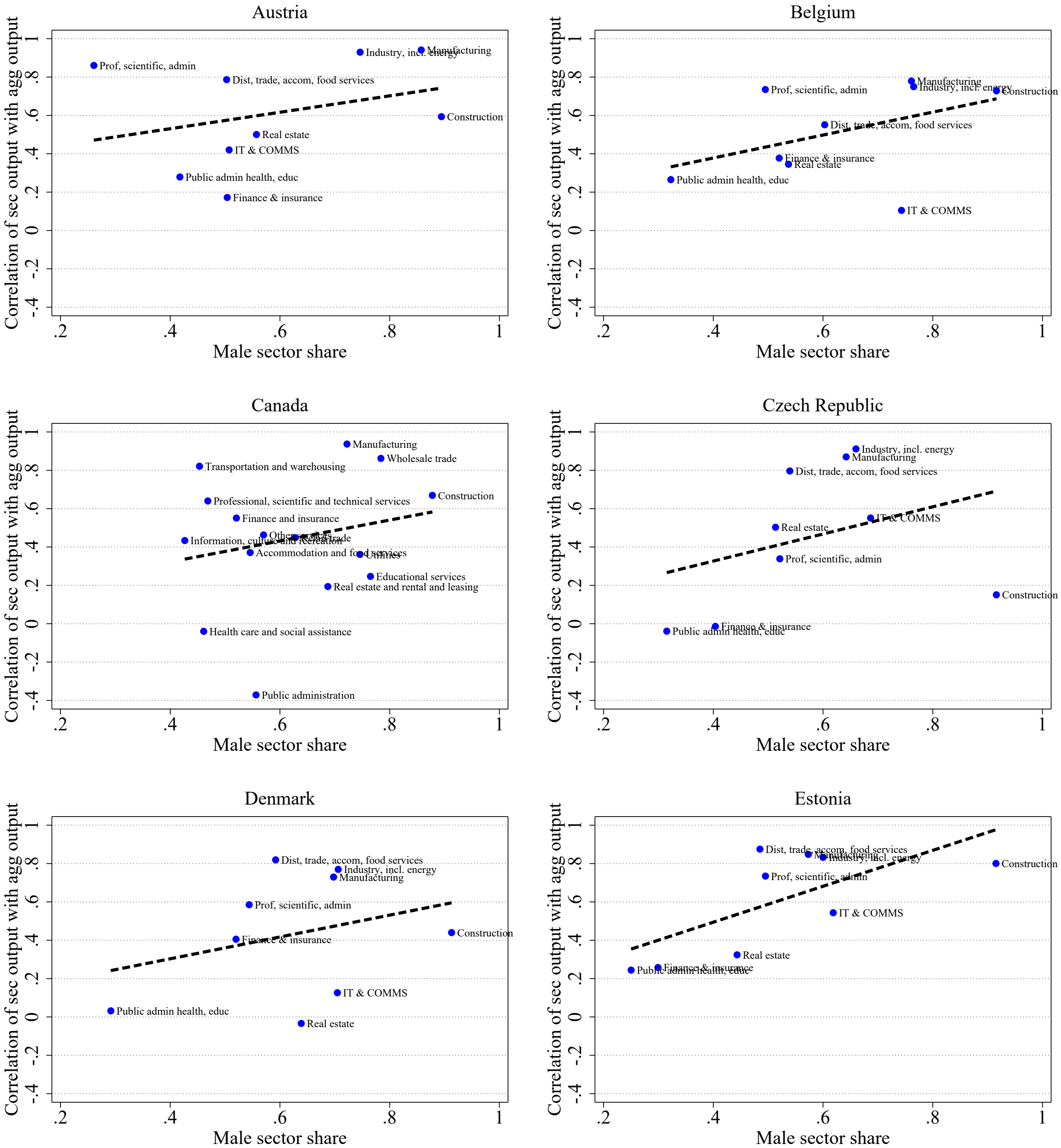
Note: The bold line represents the percentage change in unemployment for males minus the percentage change in unemployment for females. The long dashed line shows the contributions to the increase in the bold line of differences in changes in the ins between males and females. The short dashed line shows the contributions to the increase in the bold line of differences in changes in the outs between males and females. Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

FIGURE B1: The contributions of the unemployment flows to the unemployment gap (cont'd)



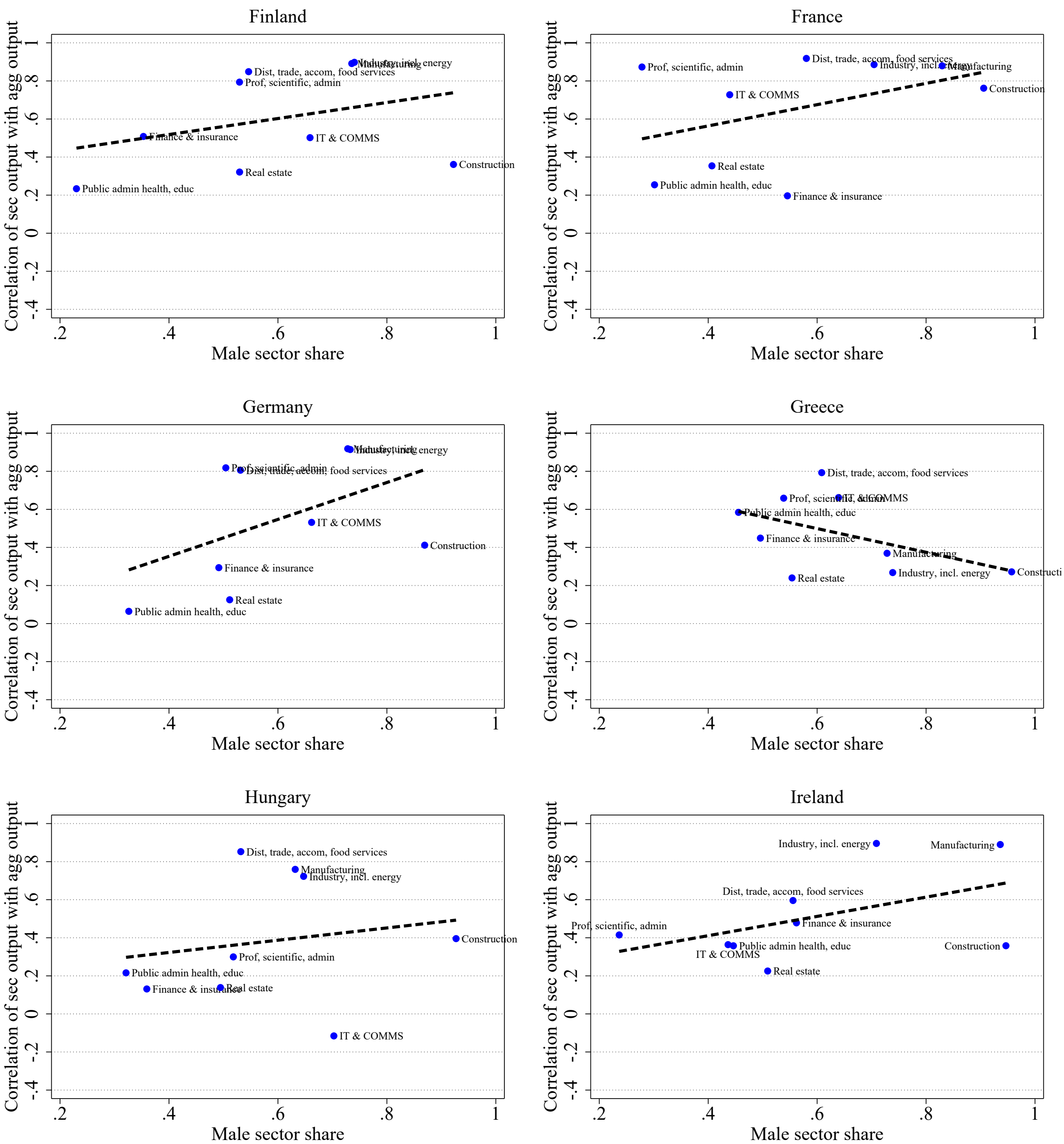
Note: The bold line represents the percentage change in unemployment for males minus the percentage change in unemployment for females. The long dashed line shows the contributions to the increase in the bold line of differences in changes in the ins between males and females. The short dashed line shows the contributions to the increase in the bold line of differences in changes in the outs between males and females. Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

FIGURE B2: Relationship between male share and the correlation of sector output with overall output by country



Note: Excluded agricultural sector.

FIGURE B1: Relationship between male share and the correlation of sector output with overall output by country (cont'd)



Note: Excluded agricultural sector.

FIGURE B1: Relationship between male share and the correlation of sector output with overall output by country (cont'd)

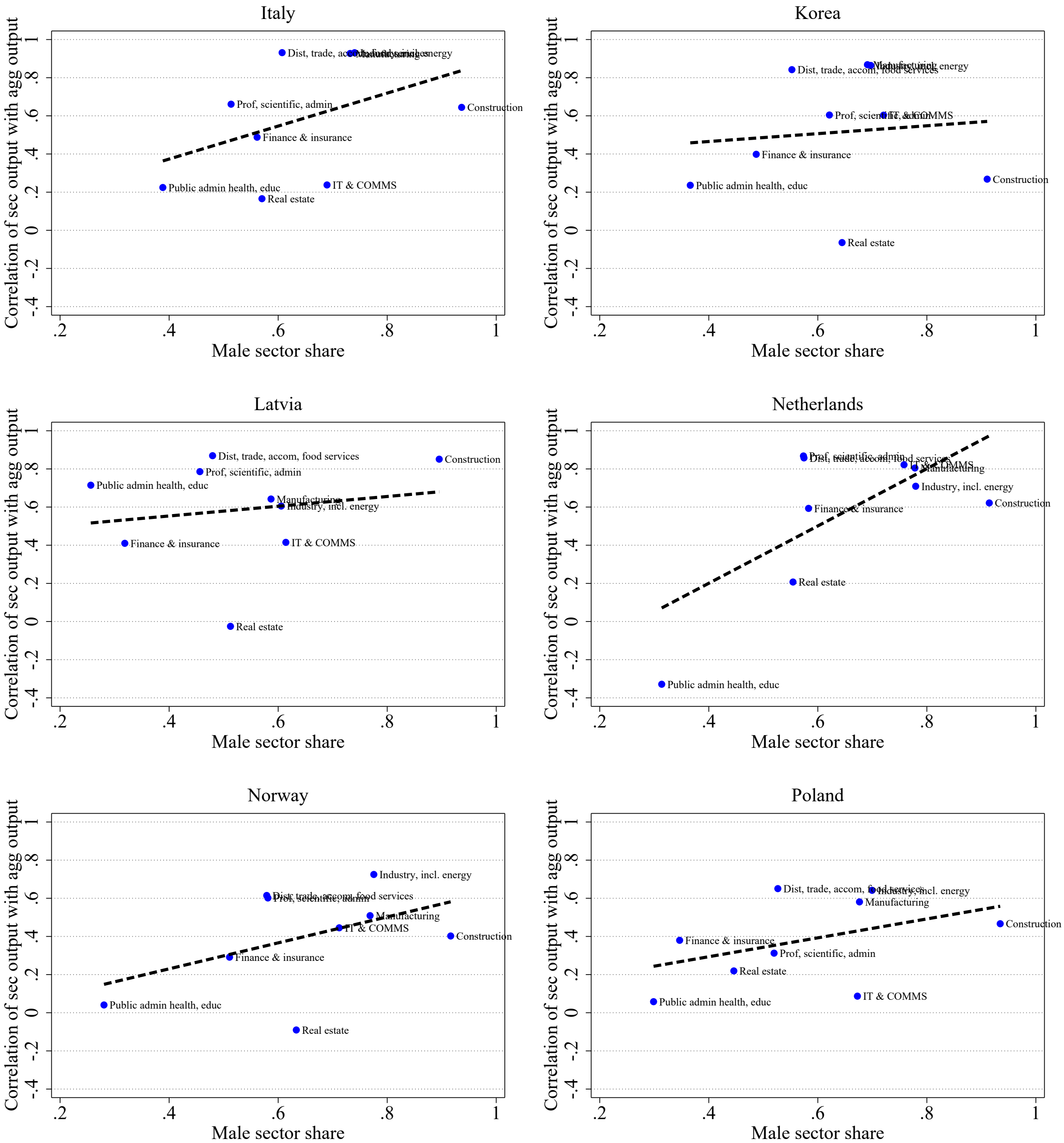
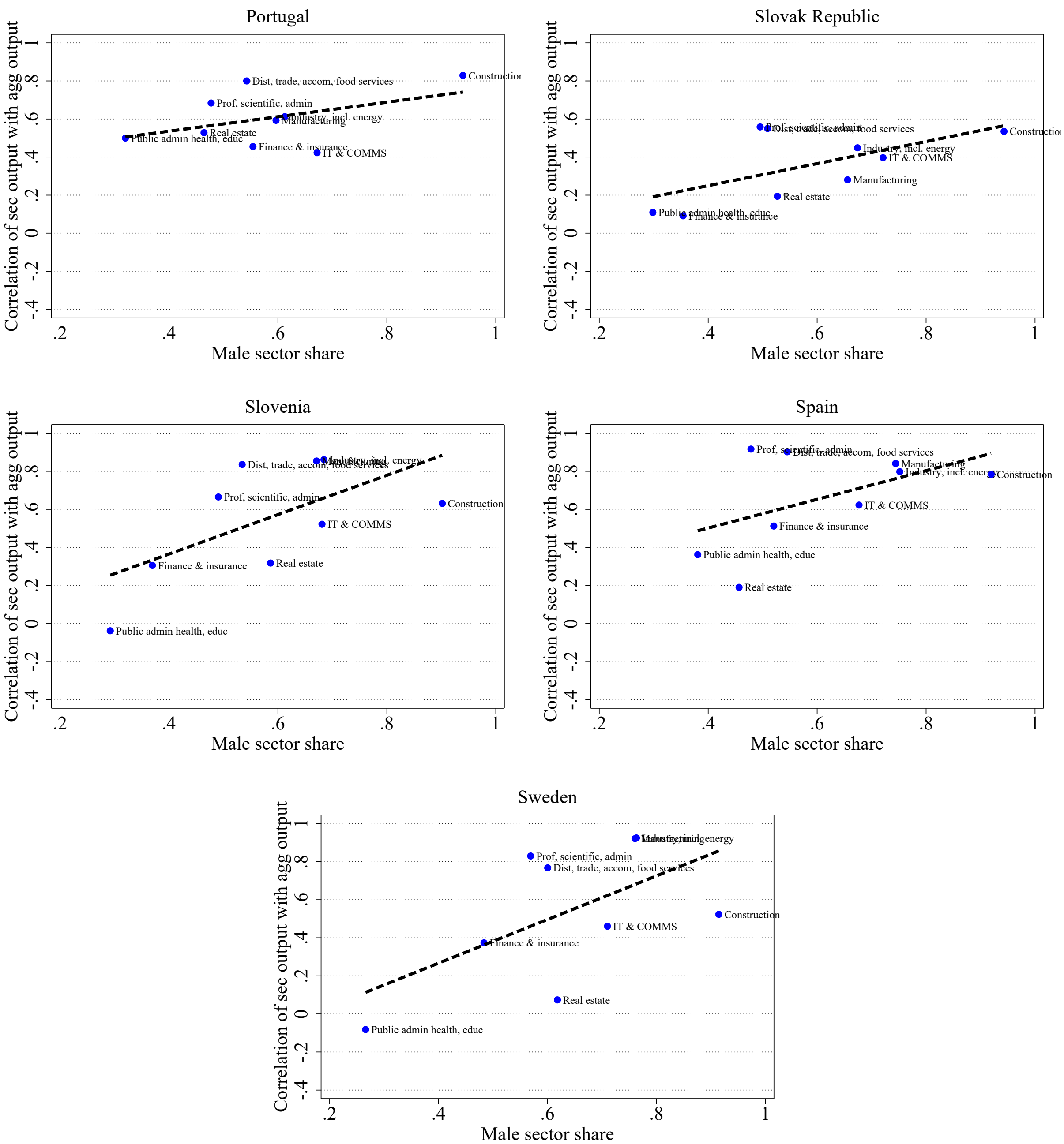


FIGURE B2: Relationship between male share and the correlation of sector output with overall output by country continued

Note: Excluded agricultural sector.

FIGURE B1: Relationship between male share and the correlation of sector output with overall output by country(cont'd)



Note: Excluded agricultural sector.

Online appendix for "The ins and outs of the gender unemployment gap in the OECD"

Reamonn Lydon   Michael Simmons [*]

1 Further information on the outflow estimation process

For completeness, here we provide more information regarding the estimation process for the unemployment outflow. It should be made clear that this process exactly follows Elsby et al. (2013), but by gender, and is not a contribution of this paper. One does not have to use information on unemployment duration of less than one month to estimate the monthly outflow rate. The OECD provides information on unemployment duration of less than one, three, six and twelve months. To see how any of these duration methods can be used to estimate the monthly unemployment outflow rate, begin with

$$u_{t+d} - u_t = u_{t+d}^{<d} - F_t^{<d} u_t. \tag{1}$$

where $u_{t+d}^{<d}$ is the percentage of the unemployed at time $t+d$ and have been there for less than d months, and $F_t^{<d}$ is the probability of leaving unemployment in less than d months. Rearranging, we find

$$F_t^{<d} = 1 - \frac{u_{t+d} - u_{t+d}^{<d}}{u_t}, \tag{2}$$

which relates to the corresponding monthly outflow rate as

$$f_t^{<d} = \frac{-ln(1 - F_t^{<d})}{d}, \tag{3}$$

leaving us with outflow rate measures $f_t^{<1}$,$f_t^{<3}$, $f_t^{<6}$, and $f_t^{<12}$. The aim is to use a weighted sum of these outflows as f_t. Notice that these rates are not necessarily the same. If $f_t^{<1} > f_t^{<3} > f_t^{<6} > f_t^{<12}$, or the outflow rate exhibits negative duration dependence, then estimates of the outflow rates with large durations, for example $f_t^{<12}$, will not provide consistent estimates of the aggregate outflow rates. Only when duration dependence is not present, can all information on unemployment durations be used.

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Before we test for duration dependence define the following two vectors

$$\mathbf{f}_t = \begin{bmatrix} f_t^{<1} & f_t^{<3} & f_t^{<6} & f_t^{<12} \end{bmatrix}' \tag{4}$$

and

$$\mathbf{u}_t = \begin{bmatrix} u_{1,t} & u_{3,t} & u_{6,t} & u_{12,t} & u_{\infty,t} & u_{t-3} & u_{t-6} & u_{t-12} \end{bmatrix}', \tag{5}$$

and let $\mathbf{V}_t$ be the associated covariance matrix of $\mathbf{u}_t$. $u_{1,t}$ is the fraction of the unemployed who have been unemployed for less than one month, $u_{3,t}$ is the fraction of the unemployed who have been unemployed for less than three months but more than one month, $u_{6,t}$ is the fraction of the unemployed who have been unemployed for less than six months but more than three months, $u_{12,t}$ is the fraction of the unemployed who have been unemployed for less than twelve months but more than size months, $u_{\infty,t}$ is the fraction of the unemployed who have been unemployed for more than twelve months. u_{t-3}, for example, is the unemployment rate at time $t-3$.

With the covariance matrix in hand, it is possible to use the Delta-method to write down the approximate distribution of $\hat{\mathbf{f}}_t$ as $\hat{\mathbf{f}}_t \sim N(\mathbf{f}_t, \frac{1}{n} D_{f,t} V_t D'_{f,t})$, where $D_{f,t}$ is the gradient matrix as in Elsby et al. (2013). This distribution will be used in the hypothesis test and the optimal weighting of the four outflow measures for the estimated outflow rate. The hypothesis test is

$$H_0:\ \mathbf{f}_t = f\mathbf{i}, \tag{6}$$

where f is a scalar, $\mathbf{i}$ is a vector of ones. Using

$$M_f = \begin{bmatrix} 1 & 0 & 0 & -1 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & -1 \end{bmatrix} \tag{7}$$

under the null-hypothesis, it is the case that $\mathbf{M}_f \hat{\mathbf{f}}_t \sim N(0, \frac{1}{n} \mathbf{M}_f \mathbf{D}_{f,t} \mathbf{V}_t \mathbf{D}'_{f,t} \mathbf{M}'_f$. It follows that $g_t \sim \chi^2(3)$, where $g_t = n\hat{\mathbf{f}}' \mathbf{M}'_f (\mathbf{M}_f \mathbf{D}_{f,t} \mathbf{V}_t \mathbf{D}'_{f,t} \mathbf{M}'_f)^{-1} \mathbf{M}_f \hat{\mathbf{f}}_t$.

For the test we need the number of individuals in each survey. For the countries that crossover with Elsby et al. (2013), we use the same n but divided by 2 for males and females. For Belgium the number of households interviewed is approximately 14,625, so we use $n = 16,750$. For Denmark the number of individuals interviewed is approximately 40,000 so $n = 20,000$. For Luxembourg, the number of households interviewed is approximately 11,250, so we use $n = 13,500$. Finally, for Netherlands, the number of households interviewed is approximately 50,000, so we use $n = 58750$. We test the null at the 5% significance level. See Table 1 for the results. The results for the male sample are to reject the null for Australia, Canada, France, Netherlands, Spain and the US. The results are fortunately the same for the female sample but that for the Netherlands the hypothesis is not rejected. For countries where the null is rejected, we use $f_t^{<1}$ as the outflow rate. For the case of the

Netherlands, for both males and females, we use $f_t^{<1}$ as my estimate for the unemployment outflow rate.

TABLE 1: The approximate number of individuals in each survey and the outcome of the hypothesis test for each country

	n	Male		Female	
		P-value	H0 Rejected?	P-value	H0 Rejected?
Australia	28,500	1.9	Yes	0.8	Yes
Belgium	16,750	49.3		32.1	
Canada	67,500	0.0	Yes	0.0	Yes
Denmark	20,000	10.2		10.4	
France	75,000	4.7	Yes	1.7	Yes
Germany	82,500	11.6		15.6	
Ireland	48,750	23.4		21.0	
Italy	30,000	52.8		21.9	
Japan	50,000	48.4		39.1	
Luxembourg	13,500	68.9		49.2	
Netherlands	58,750	9.1		2.1	Yes
New Zealand	20,000	12.1		5.0	
Norway	12,000	35.8		32.2	
Portugal	26,250	28.6		24.5	
Spain	92,500	0.1	Yes	0.0	Yes
Sweden	10,000	27.8		26.5	
United Kingdom	60,000	8.7		7.6	
United States	65,000	0.0	Yes	0.0	Yes

Note: n is based on the respective labour force surveys and when there is overlap corresponds to the same numbers used in Elsby et al. (2013) divided by 2. For Netherlands, we proceed assuming that the test was also rejected for Males.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

If the null is not rejected we calculate optimal weights following Elsby et al. (2013). We want to pick the vector of weights, $\mathbf{w}$, to estimate

$$\hat{f}_t = \mathbf{w}_t'\hat{\mathbf{f}}_t \; s.t. \; \mathbf{w}_t'\mathbf{i} = 1, \tag{8}$$

i.e. the estimated aggregate outflow, is a weighted sum of the four outflow measures. Given this constraint, $\mathbf{w}$ minimises

$$V_{f,t} = \mathbf{w}_t'\mathbf{D}_{f,t}\mathbf{V}_t\mathbf{D}_{f,t}'\mathbf{w}_t. \tag{9}$$

To take care of the constraint, define the vector

$$\tilde{\mathbf{w}}_t = \begin{bmatrix} w_t^{<1} & w_t^{<3} & w_t^{<6} \end{bmatrix}, \tag{10}$$

so $w_t^{<12}$ is 1, less the sum of the other three weights. The objective function can be written as:

$$V_{f,t} = \mathbf{e}_1'\mathbf{D}_{f,t}\mathbf{V}_t\mathbf{D}_{f,t}'\mathbf{e}_1 + 2\mathbf{e}_1'\mathbf{D}_{f,t}\mathbf{V}_t\mathbf{D}_{f,t}'\mathbf{M}_w\tilde{\mathbf{w}}_t + \tilde{\mathbf{w}}_t'\mathbf{M}_w'\mathbf{D}_{f,t}\mathbf{V}_t\mathbf{D}_{f,t}'\mathbf{M}_w\tilde{\mathbf{w}}_t, \tag{11}$$

which results in the optimal set of weights as:

$$\tilde{\mathbf{w}}_t = -(\mathbf{M}_w'\mathbf{D}_{f,t}\mathbf{V}_t\mathbf{D}_{f,t}'\mathbf{M}_w)^{-1}\mathbf{M}_w'\mathbf{D}_{f,t}\mathbf{V}_t\mathbf{D}_{f,t}'\mathbf{e}_1. \tag{12}$$

2 Further mathematical details

This section of the online appendix provides formal derivations of key equations in the paper.

Unemployment and steady state

Here we describe how one of the main equations in the text is obtained, first shown in Shimer (2012),

$$u_t = \left(1 - e^{-12(s_t+f_t)}\right)u_t^* + e^{-12(s_t+f_t)}u_{t-12}. \tag{13}$$

Start with

$$\frac{du_t}{dt} = s_t(1-u_t) - f_t u_t \Rightarrow \frac{du_t}{dt} + (s_t+f_t)u_t = s_t. \tag{14}$$

This is a first order linear differential equation in u. If we make the assumption that flows are not changing within a period, say τ months, the solution can be written as

$$u_t = e^{-\tau(f_t+s_t)} + ce^{-\tau(f_t+s_t)}, \tag{15}$$

where c is the constant of integration. c represents initial deviations from steady state $c = u_t^* - u_{t-\tau}$. Substiting c into (15) and setting $\tau = 12$ months gives (13).

Non-logarithmic decomposition

In order to asses deviations in unemployment rates as opposed to logarithmic deviations we write down a decomposition in levels. Begin with (13)

$$u_t = \left(1 - e^{-12(s_t+f_t)}\right)u_t^* + e^{-12(s_t+f_t)}u_{t-12}. \tag{16}$$

First-differencing and letting $e^{-12(s_t+f_t)} \approx e^{-12(s_{t-1}+f_{t-1})}$, we have

$$\Delta u_t = (1 - e^{-12(s_t+f_t)})\Delta u_t^* + e^{-12(s_t+f_t)}\Delta u_{t-12} + \varepsilon. \tag{17}$$

Now all we need is a categorisation for Δu_t^*. As is shown in Petrongolo and Pissarides (2008) and Smith (2012), among others, it is straightforward to show that

$$\Delta u_t^* = (1-u_t^*)u_{t-12}^* \frac{\Delta s_t}{s_{t-12}} - (1-u_{t-12}^*)u_t^* \frac{\Delta f_t}{f_{t-12}}. \tag{18}$$

We show the derivation for completeness. Begin with the twelve month changes in unemployment

$$\Delta u_t^* = \frac{s_t}{s_t+f_t} - \frac{s_{t-12}}{s_{t-12}+f_{t-12}} = \frac{s_t(s_{t-12}+f_{t-12}) - s_{t-12}(s_t+f_t)}{(s_t+f_t)(s_{t-12}+f_{t-12})} = \frac{s_t f_{t-12} - s_{t-12} f_t}{(s_t+f_t)(s_{t-12}+f_{t-12})}. \tag{19}$$

Including $s_t f_t - s_t f_t$ in the numerator we have

$$\begin{aligned} \Delta u_t^* &= \frac{s_t f_t - s_t f_t + s_t f_{t-12} - s_{t-12} f_t}{(s_t+f_t)(s_{t-12}+f_{t-12})} = \frac{\Delta s_t f_t}{(s_t+f_t)(s_{t-12}+f_{t-12})} + \frac{\Delta f_t s_t}{(s_t+f_t)(s_{t-12}+f_{t-12})} \\ &= \frac{\Delta s_t}{s_{t-12}} \frac{f_t}{s_t+f_t} \frac{s_{t-12}}{s_{t-12}+f_{t-12}} + \frac{\Delta f_t}{f_{t-12}} \frac{s_t}{s_t+f_t} \frac{f_{t-12}}{s_{t-12}+f_{t-12}}, \end{aligned} \tag{20}$$

which is equivalent to (18), where the final equality follows from multiplying the first ratio by s_{t-1}/s_{t-1} and the second by f_{t-1}/f_{t-1}. Combining (17) and (18), we can write the contributions of the inflows and outflows, respectively, as

$$C_{s_t} = \left(1 - e^{-12(s_t+f_t)}\right)(1-u_t^*)u_{t-12}^* \frac{\Delta s_t}{s_{t-12}} + e^{-12(s_t+f_t)} C_{s_{t-12}}, \tag{21}$$

and

$$C_{f_t} = -\left(1 - e^{-12(s_t+f_t)}\right)(1-u_{t-12}^*)u_t^* \frac{\Delta f_t}{f_{t-12}} + e^{-12(s_t+f_t)} C_{f_{t-12}}, \tag{22}$$

where $C_{s_0} = C_{f_0} = 0$. Finally, the contribution of initial deviations is given as

$$C_{0_t} = e^{-12(s_t+f_t)} C_{0_{t-12}} \text{ with } C_{0_0} = \Delta u_0. \tag{23}$$

Smith (2012) also provides a non-logarithmic decomposition. We have found that when using her decomposition, the errors are large, so we resort to this decomposition. Table 2 shows the results when applying this decomposition method.

TABLE 2: Contributions to unemployment variations for males and females using the non-logarithmic decomposition

	Males				Females			
	β_f	β_s	β_0	β_ε	β_f	β_s	β_0	β_ε
Australia	0.24	0.77	0.00	-0.01	0.50	0.50	0.00	0.00
Belgium	0.56	0.41	0.00	0.03	0.60	0.28	-0.01	0.13
Canada	0.60	0.40	0.00	0.00	0.66	0.34	0.00	0.00
Denmark	0.41	0.60	0.01	-0.01	0.39	0.62	0.00	-0.01
France	0.71	0.21	0.02	0.06	0.89	0.05	0.02	0.04
Germany	0.51	0.48	0.03	-0.02	0.81	0.12	0.12	-0.05
Ireland	0.65	0.34	0.03	-0.01	0.66	0.28	0.05	0.01
Italy	0.60	0.33	0.00	0.06	0.58	0.30	0.03	0.10
Japan	0.42	0.58	0.00	0.00	0.36	0.63	0.00	0.01
Luxembourg	0.59	0.47	0.00	-0.05	0.07	0.92	0.01	0.00
Netherlands	0.15	0.82	-0.02	0.05	0.29	0.80	-0.01	-0.07
New Zealand	0.66	0.68	0.00	-0.35	0.56	0.57	0.00	-0.13
Norway	0.42	0.56	0.00	0.02	0.43	0.56	0.00	0.01
Portugal	0.49	0.53	0.00	-0.02	0.52	0.41	0.00	0.07
Spain	0.48	0.51	0.03	-0.02	0.51	0.57	-0.02	-0.07
Sweden	0.32	0.68	0.00	-0.00	0.16	0.81	0.00	0.02
United Kingdom	0.50	0.49	0.00	0.01	0.93	0.03	0.01	0.03
United States	0.72	0.28	0.00	0.00	0.78	0.22	0.00	0.00
Average	0.50	0.51	0.01	-0.01	0.54	0.45	0.01	0.01

Note: The interpretation of the male results for Australia are: Variations in the outflows contribute to 24% of the dynamics of the unemployment rate, variations in the inflows contribute to 77% of the dynamics of the unemployment rate, 0% of the dynamics of the unemployment rate can be attributed to initial deviations from steady-state, and changes in the error contribute to -2% of the dynamics of the unemployment rate.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

3 Steady-state vs non-steady-state

If the economy remains in steady-state in all periods notice that the baseline decomposition in the text collapses to:

$$\Delta ln(u_t) = (1 - u^*_{t-1})[\Delta ln s_t - \Delta ln f_t] + \varepsilon. \tag{24}$$

Table 3 shows the results when using the steady-state and non-steady-state decomposition for males and females. The steady-state decomposition is not suitable for two reasons. First because flows are relatively small for many of the countries, the convergence to steady-state is slow. This results in very large errors as we can see. Secondly, because the unemployment flows are, in general, slightly larger for females relative to males, the convergence to steady-state is quicker for females relative to males. This is likely to result in slightly larger errors for males relative to females. We can see that this is in general true - the average absolute value of the error for males and females is 0.35 and 0.31, respectively.

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TABLE 3: Contributions to unemployment variation

	Steady-state						Non-steady-state							
	Males			Females			Males				Females			
	β_f	β_s	β_ε	β_f	β_s	β_ε	β_f	β_s	β_0	β_ε	β_f	β_s	β_0	β_ε
Australia	0.38	0.73	-0.11	0.53	0.51	-0.04	0.37	0.66	0.00	-0.02	0.53	0.48	0.00	-0.01
Belgium	1.14	0.59	-0.73	0.93	0.91	-0.85	0.53	0.38	0.00	0.09	0.59	0.44	0.00	-0.03
Canada	0.60	0.42	-0.02	0.67	0.34	-0.01	0.60	0.42	0.00	-0.01	0.66	0.34	0.00	-0.01
Denmark	0.46	0.71	-0.17	0.39	0.82	-0.21	0.38	0.61	0.00	0.00	0.34	0.66	0.00	0.00
France	0.28	1.75	-1.03	-0.21	2.09	-0.89	0.54	0.58	0.02	-0.14	0.36	0.69	0.02	-0.07
Germany	0.69	0.75	-0.44	0.97	0.31	-0.28	0.47	0.51	0.04	-0.02	0.84	0.12	0.06	-0.02
Ireland	0.91	0.58	-0.49	0.84	0.47	-0.31	0.57	0.47	0.04	-0.10	0.67	0.35	0.03	-0.06
Italy	1.34	0.52	-0.86	1.62	0.28	-0.90	0.76	0.33	0.01	-0.10	1.01	0.11	0.02	-0.14
Japan	0.63	0.66	-0.29	0.32	0.80	-0.12	0.51	0.48	0.00	0.01	0.30	0.70	0.00	0.00
Luxembourg	1.09	0.42	-0.51	0.11	1.20	-0.31	0.69	0.31	0.01	-0.01	0.11	0.89	0.00	-0.02
Netherlands	0.23	1.11	-0.34	0.42	1.07	-0.48	0.14	0.78	0.06	-0.01	0.42	0.62	0.00	-0.01
New Zealand	0.56	0.63	-0.19	0.56	0.58	-0.14	0.49	0.57	0.05	-0.11	0.52	0.51	0.02	-0.05
Norway	0.42	0.65	-0.08	0.43	0.64	-0.07	0.39	0.60	0.00	0.00	0.41	0.58	0.00	0.00
Portugal	0.69	0.70	-0.39	0.69	0.71	-0.41	0.41	0.59	0.00	0.00	0.55	0.44	0.01	0.00
Spain	0.73	0.51	-0.24	1.13	0.16	-0.29	0.57	0.51	0.00	-0.08	0.84	0.17	0.00	-0.02
Sweden	0.29	0.81	-0.10	0.21	0.88	-0.09	0.26	0.73	0.00	0.00	0.22	0.76	0.00	0.03
United Kingdom	0.55	0.76	-0.32	0.95	0.24	-0.19	0.43	0.57	0.00	0.00	0.83	0.21	0.00	-0.04
United States	0.68	0.34	-0.02	0.79	0.22	-0.01	0.67	0.34	0.00	-0.02	0.79	0.22	0.00	-0.01

Note: The interpretation of the Male steady-state results for Australia read: Variations in the outflows contribute to 38% of unemployment variation, variations in the inflows contribute to 73% of unemployment variation, and changes in the error contribute to -11% of the variations in the unemployment rate.
Source: Author calculations based on data compiled from OECD (2018a) and OECD (2018b).

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