Declining Worker Turnover: The Role of Short-Duration Employment Spells
A comment on Pries and Rogerson (2022)*

By Alexandre Pavlov, Raphael Jananji, and Feraud Tchuisseu

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Abstract

Using a Diamond-Mortensen-Pissarides (DMP) model with noisy signals on worker-firm match quality calibrated on data from 30 US states for 1999 and 2017, Pries and Rogerson argue that improved screening may explain the decrease in short-term employment spells observed in the US labor market. Using a decomposition exercise in a "reduced form" model, the authors show that changes in short-term employment spells (δ_1 and δ_2) are almost entirely accounted for by changes in the rate of learning on match quality α and in the probability of a good match π^g. Then, using a decomposition exercise in a "structural" model, they show in their main calibration strategy that changes in δ_1 and δ_2 are mainly driven by changes in α and σ_ϵ, parameters pertaining to learning about match quality.

First, we reproduce the authors' codes in R and Python, two popular free open source programming languages. We find identical results to the paper. Second, we test the robustness of results to (1) using an earlier starting year, (2) adding additional states in the analysis, and (3) increasing the value of the 1999 mean vacancy duration parameter. The direction and relative size of the effect of each parameter on δ_1 and δ_2 is preserved in all robustness tests, corroborating the authors' argument.

JEL codes: E24, J23, J41, J63, M51.

*Authors: Alexandre Pavlov: University of Montreal. E-mail: alexandre.pavlov@umontreal.ca.
Raphael Jananji: University of Montreal. E-mail: raphael.jananji@umontreal.ca.
Feraud Tchuisseu: University of Montreal. E-mail: feraud.tchuisseu@umontreal.ca.

1 Introduction

Pries and Rogerson analyze the decline in short-term employment spells in the US between 1999 and 2017 in a DMP model with learning on match quality calibrated to labor market data on 30 states from the Quarterly Workforce Indicators (QWI) database. The authors perform decomposition exercises where they change model parameters one-by-one from their 1999 values to their 2017 values to assess the model's ability to replicate the changes in one-quarter and two-quarter hazard rates (δ_1 and δ_2) observed in the data. The authors present their main descriptive claim in the abstract as follows: "[We] argue that improved screening by workers and firms can account for much of the decline in short-lived employment spells".

To make this claim more precise, we can express it in two parts. First, they use a decomposition exercise in a "reduced form" model to show that the change in λ from the basic DMP model cannot on its own replicate the observed decrease in δ_1 and δ_2. Instead, this decrease is mainly generated by changing α and π^g. As stated in p.283:

"[The] decrease in the hazard rate for one- and two-quarter employment spells is almost entirely accounted for by changes in α and π^g [...] [The decrease in λ] cannot be the whole story because it cannot generate the observed changes in hazard rates by duration of employment spell."

Second, the authors use a decomposition exercise in a "structural" model to show that changes in the parameters of learning about match quality are important in generating decreases in δ_1 and δ_2. They summarize their main results in p.288:

"The results show that neither k_r nor A play a significant role in explaining the observed declines in any of the hazard rates [...] By contrast, σ_ϵ and α play significant roles in accounting for the declining separation hazards for one-quarter and two-quarter employment spells [...] These results support an interpretation of our reduced-form effects as suggesting an important role for better screening as a driving force behind the lower values for δ_1 and δ_2."

In this paper, we ascertain the reproducibility of their numerical results and test their robustness to: (1) using 1997 as the starting year at the expense of cutting the number of states to 18, (2) expanding the number of states to 49 at the expense of using 2006 as the starting year, and (3) using a higher value for the 1999 mean vacancy duration parameter.

For the first robustness test, we use the QWI data provided by the authors, but modify the code creating the dataset to exclude the 12 states missing 1997 data. We then modify all R codes to compare 2017 with 1997 instead of 1999. Using the summary statistics calculated in the modified file shortjobs_national_1997.R, we change the targeted moments in the "reduced form" model code shortjobs_reduced_form_1997.py. Then, using the parameter values calculated in this file (π^g, α, λ), we modify the parameters in shortjob_structural_1997.py. We also use DFI-DFH data available at FRED as well as the job finding rate estimated from BLS data provided to us by the authors to update the model parameters. We follow the same steps for the second robustness test, except that we start by downloading QWI data for all 50 states since the authors only include data for the 30 studied states in their replication package. For the third robustness test, we replace the 1999 value for the mean vacancy duration initially set to 22.8/7 by 25/7 in the code for the structural model.

Using the original paper's replication package, we successfully reproduce every table and figure of the original study. The code is well documented and can be executed almost out-of-the-box by anyone with access to a Stata license and MATLAB license as the authors also provide the relevant QWI data for the 30 states being studied. Since proprietary software may act as a barrier to reproducibility, we rewrite the authors' codes in R and Python, two popular free open source alternatives to Stata and MATLAB. We do not find any significant errors in the original codes and the output of our codes is identical to theirs.

We find that changing the initial year of the analysis to 1997 or 2006 does not change the conclusions of the decomposition exercise in the "reduced form" model. In all robustness exercises, the decrease in δ_1 is mostly accounted by the change in α and π^g while the decrease in δ_2 is mostly accounted by the change in π^g. The conclusions of the decomposition exercise in the "structural" model are also unchanged when using 1997 as the starting year: changes in α and σ_ϵ generate most of the decrease in δ_1 while changes in σ_ϵ generate most of the decrease in δ_2. This is also the case when using 2006 as the starting year. Finally, using a slightly higher value for the mean vacancy duration yields almost identical results, some values only occasionally differing in the thousandth decimal place.

2 Reproducibility

The replication package provided by Pries and Rogerson generates every table and figure in their article, with the exception of table 3. However, the values in table 3 are either calculated at different parts of the code or justified in the main text. The authors provide QWI data for the 30 states being studied and explain where to seek information on the different parameters of the model. Although they did not include the average job finding rates through 2017 in the replication package, they can be computed with public BLS data[1]. As we were unsure of the specific data and method used[2], we asked the authors for the original file they used in order to ensure consistency with the original paper in setting the average job finding rate for 1997 and 2006. We thank the authors for providing us with this data.

To improve the reproducibility of the study and to better detect possible coding errors, we have rewritten the programs in the replication package in R and Python, which are respectively popular free open source alternatives to Stata and MATLAB. We used the original codes as a guide while also cross-referencing them with the paper. Since the codes are fairly well-commented and the README explains what each file does, this task was relatively simple. No coding errors were found and the output from our ported codes is essentially identical to their original counterparts. The authors' codes and data are available here while ours are available here.

[1] https://www.bls.gov/cps/cpsdbtabs.htm

[2] Our estimates using BLS data and the method described in p.58 of Engbom (2018) were slightly off from the authors' in a previous version of this paper, though this did not significantly affect the final results.

3 Replication

Because some states have no data for earlier years, the authors had to choose the starting year in a trade-off between spatial coverage and temporal coverage. Though they ended up choosing 1999 and 30 states, they could have chosen to start at an earlier date at the expense of removing some states from their analysis or to add more states at the expense of starting their analysis at a later year. Therefore, we conduct two robustness replications to ensure that the results are not sensitive to the choice of the initial year or the states covered. First, we use 1997 as an alternative initial year of the analysis. Doing so comes at the expense of cutting 12 states: Florida, Georgia, Indiana, North Dakota, Nevada, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Virginia. This leaves us with 18 states representing about 50% of US employment. Second, we use 2006 as the initial year of the analysis. This allows us to use 49 states instead of the original 30, increasing coverage from about two thirds of US employment to about 97% of US employment. Massachusetts is the only outlier. Hence, we get almost total representation of the US labor market at the expense of covering a smaller time period. While it is possible to start at an earlier date and still make good gains in the number of covered states, doing so puts us closer to the early 2000s recession and the subsequent recovery period. Ideally, we would want the starting year to be at full-employment like the the final year so that the two labor markets differ as little as possible, except possibly for the characteristics being studied. The starting dates for the two robustness replications were chosen after downloading QWI data for all 50 states and tallying the states with missing data per year.

In the original study, the authors had to use the first 6 months of 2001 to set the 1999 value for the mean vacancy duration parameter due to data not being available before 2001. However, because 2001 is right after the dot-com crash, the 2001 mean vacancy duration might have been higher than the actual 1999 value. As a final robustness test, we redo the numerical exercises with a slightly higher mean vacancy duration. We pick 25/7 as the alternate mean vacancy duration instead of 22.8/7. The precise value is arbitrary, but likely within a reasonable range of what the 1999 value might have been.

3.1 Decomposition results in reduced form model

3.1.1 1997 start date We first investigate whether calibrating the initial steady state to 1997 data has an impact on the signs and relative magnitudes of the effect of changing different parameters on δ_1 and δ_2 in the "reduced form" model decomposition exercise. We focus on these two variables as the main argument of the original study pertains to short-term employment spells, but we still replicate all the tables from the original study with the new data in Appendix A.3. We do the same for 2006 in Appendix A.4.

Starting with 1997 cuts the number of states from the original 30 to 18, leaving California, Colorado, Connecticut, Hawaii, Illinois, Kansas, Louisiana, Maryland, Maine, Minnesota, Missouri, Montana, North Carolina, New Jersey, New Mexico, Texas, Washington, and West Virginia. Together, these remaining states represent about 50% of US employment.

We present the main results in Column 3 of Table 4.0.1. In terms of signs and relative magnitudes, the results align with those of the authors. Like in the original paper, changes in α and π^g generate most of the decrease in δ_1 and changes in π^g generate most of the decrease in δ_2.

3.1.2 2006 start date Next, we move the starting date forward to incorporate data from more US states. Although 2001 already allows us to use 42 states (92% of US employment), it is marked by a recession. Since the objective is to compare two full-employment years (i.e., years distinguished mainly by structural differences in the job market rather than cyclical variations), we choose 2006 as an alternate initial year. 1999 and 2006 are similar in having the lowest unemployment rate in their respective cycle and immediately preceding the next recession.

Moving the initial steady state to 2006 allows us to include all US states except for Massachusetts and thus cover about 97% of US employment. We present the main results in Column 4 of Table 4.0.1. Just like before, the signs and relative magnitudes roughly align with those of the others.

3.2 Decomposition results in structural model

3.2.1 1997 start date We continue on with the decomposition exercise in the "structural" model. As in the previous subsection, we focus on δ_1 and δ_2. This amounts to replicating the first two columns of Table 6 from the original study. Column 3 of Table 4.0.2 reports the results. Consistent with the original study, the changes in k_r and A have a negligible effect on δ_1 and δ_2. On the other hand, most of the change in δ_1 is accounted for by changes in α and σ_ϵ while most of the change in δ_2 is accounted for by changes in σ_ϵ. One minor difference with the original study is that the effect of α on δ_1 is larger than that of σ_ϵ rather than the other way around. This does not contradict the authors' argument, however.

3.3 2006 start date

Next, we look at the potential effect of expanding geographic scope of the study and pushing forward the starting year. We present our results in Column 4 of Table 4.0.2. This time, the change in k_r has a small negative effect on δ_1 and δ_2. The change in A also has a slightly larger effect on δ_1 than λ and a comparable effect on δ_2 to that of λ. However, the most important parameters remain α and σ_ϵ. Hence, the main conclusion on the decrease in δ_1 and δ_2 being mainly driven by a change in parameters pertaining to learning on match quality still holds.

3.4 Higher 1999 mean vacancy duration

Finally, we explore the impact of adjusting the 1999 mean vacancy duration parameter upwards. The original paper uses the average mean vacancy duration for the first half of 2001, given that 1999 data was unavailable. However, considering the aftermath of the dot-com bubble burst in 2000, it is plausible that the actual mean vacancy duration for 1999 was higher than the 2001 value. As a result, we propose a hypothetical mean vacancy duration of 25/7 instead of the original 22.8/5. The specific value is arbitrary but likely within a reasonable range of values the actual 1999 mean vacancy duration might have fallen in.

We present our results in Column 5 of table 4.0.2. The results are almost the same as those of the original paper, with only minor changes in the thousandth decimal place k_r and A. Based on this, we conclude that the usage of 2001 data for the mean vacancy duration – despite a time period being bookended by the dot-bubble crash and the 2001 recession – is unlikely to have skewed the results.

4 Conclusion

In this replication study, we have translated the original research code into R and Python, extending its accessibility to researchers who may not hold licenses for Stata or MATLAB. We have then performed three robustness exercises, pushing back the starting year to 1997, extending the number of states to 49, and increasing the 1999 the mean vacancy duration. The first two robustness checks are made to ensure that the results are not sensitive to the authors' choice of starting date or their choice of the number of states. The last robustness check verifies whether the choice to use 2001 values for the mean vacancy duration rather than a higher value significantly affects the results. We find that the signs and relative magnitudes of the effects of varying parameters on short-term hazard rates remain consistent in all robustness tests.

References

[1] United States Census Bureau. *Longitudinal Employer-Household Dynamics*. 2023. URL: https://lehd.ces.census.gov/data/.

[2] N. Engbom. "Firm and Worker Dynamics in an Aging Labor Market". In: *Society for Economic Dynamics 2018 Meeting Papers 1009*.

[3] DHI Group Inc. *DHI-DFH Mean Vacancy Duration Measure*. 2018. URL: https://fred.stlouisfed.org/series/DHIDFHMVDM.

[4] J. Pries and R. Rogerson. "Declining Worker Turnover : The Role of Short-Duration Employment Spells". In: *American Economic Journal: Macroeconomics* 14.1 (2022), pp. 260–300.

Table 4.0.1: Decomposition results in reduced form model: changing start year

	Original		R & Python		1997 start		2006 start	
	$\Delta\delta_1$	$\Delta\delta_2$	$\Delta\delta_1$	$\Delta\delta_2$	$\Delta\delta_1$	$\Delta\delta_2$	$\Delta\delta_1$	$\Delta\delta_2$
Data	-0.060	-0.040	-0.060	-0.040	-0.050	-0.040	-0.033	-0.020
π^g, α, λ change	-0.060	-0.040	-0.060	-0.040	-0.049	-0.040	-0.033	-0.020
Only π^g changes	-0.025	-0.031	-0.025	-0.031	-0.026	-0.033	-0.014	-0.017
Only α changes	-0.030	0.006	-0.030	0.006	-0.019	0.004	-0.016	0.004
Only λ changes	-0.007	-0.015	-0.007	-0.015	-0.005	-0.011	-0.003	-0.006

Notes: Authors' calculations using data from 1997 to 2017 from the Quarterly Workforce Indicators database. Each observation is an employee-employer pair. The third column uses 18 states (removing FL, GA, IN, ND, NV, PA, RI, SC, SD, TN, VA) and the fourth column uses 49 states (MA data is unavailable until 2010).

Table 4.0.2: Decomposition result in structural model: changing start year and mvd

	Original		R & Python		1997 start		2006 start		Higher 1999 mvd	
	$\Delta\delta_1$	$\Delta\delta_2$	$\Delta\delta_1$	$\Delta\delta_2$	$\Delta\delta_1$	$\Delta\delta_2$	$\Delta\delta_1$	$\Delta\delta_2$	$\Delta\delta_1$	$\Delta\delta_2$
Data	-0.060	-0.040	-0.060	-0.040	-0.050	-0.040	-0.033	-0.020	-0.060	-0.040
k_r	0.002	0.002	0.002	0.002	0.000	0.000	-0.002	-0.003	0.002	0.003
A	0.003	0.004	0.003	0.004	0.001	0.002	0.005	0.006	0.002	0.003
λ	-0.007	-0.015	-0.007	-0.015	-0.006	-0.012	-0.003	-0.007	-0.007	-0.015
α	-0.032	0.002	-0.032	0.002	-0.021	0.002	-0.019	-0.000	-0.032	0.002
σ_ϵ	-0.028	-0.035	-0.028	-0.035	-0.025	-0.031	-0.015	-0.018	-0.028	-0.035

Notes: Authors' calculations using data from 1997 to 2017 from the Quarterly Workforce Indicators database. Each observation is an employee-employer pair. The third column uses 18 states (removing FL, GA, IN, ND, NV, PA, RI, SC, SD, TN, VA) and the fourth column uses 49 states (MA data is unavailable until 2010). The fifth column raises the 1999 mean vacancy duration from 22.8/7 to 25/7.

A Appendix Tables

A.1 Original study tables

Table A.1.1: Fit of the three-parameter model to the 1999 data

	δ_1	δ_2	δ_3	h
Data (1999)	0.387	0.383	0.112	0.215
$\pi^g = 0.419, \alpha = 0.146, \lambda = 0.0085$	0.387	0.383	0.112	0.200

Table A.1.2: Accounting for the changes in the data with changes in all three parameters

	δ_1	δ_2	δ_3	h
Data (1999 vs 2017)	-0.060	-0.040	-0.020	-0.049
$\pi^g = 0.463, \alpha = 0.124, \lambda = 0.0068$	-0.060	-0.040	-0.020	-0.046
$\pi^g = 0.463, \alpha = 0.146, \lambda = 0.0085$	-0.025	-0.031	-0.001	-0.014
$\pi^g = 0.419, \alpha = 0.124, \lambda = 0.0085$	-0.030	0.006	0.003	-0.002
$\pi^g = 0.419, \alpha = 0.146, \lambda = 0.0068$	-0.007	-0.015	-0.022	-0.032

Table A.1.3: Moments of interest: data and calibrated model, 1999

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data (1999)	0.387	0.383	0.112	0.215	0.486	3.24	0.042
Model (1999)	0.387	0.383	0.112	0.200	0.486	3.24	0.110

Table A.1.4: Parameter values and model fit, 2017 calibration
$k_r = 0.951$, $A = 0.197$, $\lambda = 0.0068$, $\alpha = 0.124$, $\sigma_\epsilon = 0.555$

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data (2017)	0.327	0.343	0.092	0.166	0.364	4.01	0.043
Model (2017)	0.327	0.343	0.092	0.154	0.364	4.01	0.115

Table A.1.5: Understanding the changes between 1999 and 2017

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data: Δ 1999-2017	-0.060	-0.040	-0.020	-0.049	-0.122	0.771	0.001
k_r	0.002	0.002	0.000	0.001	-0.029	-0.303	0.008
A	0.003	0.004	0.000	0.002	-0.059	0.427	0.018
λ	-0.007	-0.015	-0.021	-0.032	0.011	0.126	-0.021
α	-0.032	0.002	0.003	-0.004	-0.010	0.045	0.000
σ_ϵ	-0.028	-0.035	-0.001	-0.016	-0.049	0.0501	0.004

A.2 Python & R tables

Table A.2.1: Fit of the three-parameter model to the 1999 data

	δ_1	δ_2	δ_3	h
Data (1999)	0.387	0.383	0.112	0.215
$\pi^g = 0.419, \alpha = 0.146, \lambda = 0.0085$	0.387	0.383	0.112	0.200

Table A.2.2: Accounting for the changes in the data with changes in all three parameters

	δ_1	δ_2	δ_3	h
Data (1999 vs 2017)	-0.060	-0.040	-0.020	-0.049
$\pi^g = 0.463, \alpha = 0.124, \lambda = 0.0068$	-0.060	-0.040	-0.020	-0.046
$\pi^g = 0.463, \alpha = 0.146, \lambda = 0.0085$	-0.025	-0.031	-0.001	-0.014
$\pi^g = 0.419, \alpha = 0.124, \lambda = 0.0085$	-0.030	0.006	0.003	-0.002
$\pi^g = 0.419, \alpha = 0.146, \lambda = 0.0068$	-0.007	-0.015	-0.022	-0.032

Table A.2.3: Moments of interest: data and calibrated model, 1999

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data (1999)	0.387	0.383	0.112	0.215	0.486	3.24	0.042
Model (1999)	0.387	0.383	0.112	0.200	0.486	3.24	0.110

Table A.2.4: Parameter values and model fit, 2017 calibration
$k_r = 0.951$, $A = 0.197$, $\lambda = 0.0068$, $\alpha = 0.124$, $\sigma_\epsilon = 0.555$

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data (2017)	0.327	0.343	0.092	0.166	0.364	4.01	0.043
Model (2017)	0.327	0.343	0.092	0.154	0.364	4.01	0.115

Table A.2.5: Understanding the changes between 1999 and 2017 (R & Python)

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data: Δ 1999-2017	-0.060	-0.040	-0.020	-0.049	-0.122	0.771	0.001
k_r	0.002	0.002	0.000	0.001	-0.029	-0.303	0.008
A	0.003	0.004	0.000	0.002	-0.059	0.426	0.018
λ	-0.007	-0.015	-0.021	-0.032	0.011	0.126	-0.021
α	-0.032	0.002	0.003	-0.004	-0.010	0.045	0.001
σ_ϵ	-0.028	-0.035	-0.001	-0.016	-0.049	0.0503	0.004

A.3 1997 start tables (18 states)

Table A.3.1: Fit of the three-parameter model to the 1997 data

	δ_1	δ_2	δ_3	h
Data (1997)	0.381	0.379	0.108	0.210
$\pi^g = 0.410, \alpha = 0.139, \lambda = 0.0079$	0.381	0.379	0.108	0.193

Table A.3.2: Accounting for the changes in the data with changes in all three parameters

	δ_1	δ_2	δ_3	h
Data (1997 vs 2017)	-0.050	-0.040	-0.016	-0.044
$\pi^g = 0.468, \alpha = 0.130, \lambda = 0.0069$	-0.049	-0.040	-0.016	-0.055
$\pi^g = 0.468, \alpha = 0.144, \lambda = 0.0082$	-0.026	-0.033	-0.001	-0.031
$\pi^g = 0.422, \alpha = 0.130, \lambda = 0.0082$	-0.019	0.004	0.002	-0.018
$\pi^g = 0.422, \alpha = 0.144, \lambda = 0.0069$	-0.005	-0.011	-0.017	-0.042

Table A.3.3: Moments of interest: data and calibrated model, 1997

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data (1997)	0.381	0.379	0.108	0.210	0.422	3.24	0.045
Model (1997)	0.381	0.379	0.108	0.193	0.422	3.24	0.124

Table A.3.4: Parameter values and model fit, 2017 calibration
$k_r = 0.953$, $A = 0.200$, $\lambda = 0.0079$, $\alpha = 0.139$, $\sigma_\epsilon = 0.535$

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data (2017)	0.332	0.339	0.092	0.166	0.364	4.01	0.043
Model (2017)	0.332	0.339	0.092	0.155	0.364	4.01	0.115

Table A.3.5: Understanding the changes between 1997 and 2017

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data: Δ 1997-2017	-0.050	-0.040	-0.016	-0.044	-0.044	0.771	-0.002
k_r	0.000	0.000	0.000	0.000	-0.001	-0.016	0.000
A	0.001	0.002	0.000	0.000	-0.023	0.165	0.008
λ	-0.006	-0.012	-0.016	-0.022	0.009	0.106	-0.019
α	-0.021	0.002	0.002	-0.002	-0.005	0.027	0.000
σ_ϵ	-0.025	-0.031	-0.001	-0.013	-0.038	0.427	0.003

A.4 2006 start tables (49 states)

Table A.4.1: Fit of the three-parameter model to the 2006 data

	δ_1	δ_2	δ_3	h
Data (2006)	0.355	0.350	0.103	0.181
$\pi^g = 0.460, \alpha = 0.142, \lambda = 0.0078$	0.355	0.350	0.103	0.175

Table A.4.2: Accounting for the changes in the data with changes in all three parameters

	δ_1	δ_2	δ_3	h
Data (2006 vs 2017)	-0.033	-0.020	-0.008	-0.026
$\pi^g = 0.486, \alpha = 0.128, \lambda = 0.0071$	-0.033	-0.020	-0.008	-0.026
$\pi^g = 0.486, \alpha = 0.141, \lambda = 0.0078$	-0.014	-0.017	-0.001	-0.013
$\pi^g = 0.460, \alpha = 0.128, \lambda = 0.0078$	-0.016	0.004	0.002	-0.007
$\pi^g = 0.460, \alpha = 0.141, \lambda = 0.0071$	-0.003	-0.006	-0.009	-0.019

Table A.4.3: Moments of interest: data and calibrated model, 2006

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data (2006)	0.355	0.351	0.103	0.181	0.410	3.08	0.046
Model (2006)	0.355	0.350	0.103	0.174	0.410	3.08	0.115

Table A.4.4: Parameter values and model fit, 2017 calibration
$k_r = 0.956,\ A = 0.209,\ \lambda = 0.0071,\ \alpha = 0.128,\ \sigma_\epsilon = 0.500$

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data (2017)	0.322	0.331	0.095	0.161	0.364	4.01	0.043
Model (2017)	0.321	0.330	0.095	0.154	0.364	4.01	0.115

Table A.4.5: Understanding the changes between 2006 and 2017

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data: Δ 2006-2017	-0.033	-0.020	-0.008	-0.020	-0.045	0.927	-0.003
k_r	-0.002	-0.003	-0.000	-0.001	0.017	0.240	-0.006
A	0.005	0.006	0.000	0.002	-0.041	0.295	0.016
λ	-0.003	-0.007	-0.009	-0.013	0.004	0.054	-0.010
α	-0.019	-0.000	0.002	-0.002	-0.007	0.047	0.001
σ_ϵ	-0.015	-0.018	-0.001	-0.007	-0.020	0.212	0.001

A.5 Higher 1999 mean vacancy duration tables

Table A.5.1: Moments of interest: data and calibrated model, 1999

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data (1999)	0.387	0.383	0.112	0.215	0.486	3.57	0.042
Model (1999)	0.387	0.383	0.112	0.200	0.486	3.57	0.109

Table A.5.2: Parameter values and model fit, 2017 calibration
$k_r = 0.951,\ A = 0.197,\ \lambda = 0.0068,\ \alpha = 0.124,\ \sigma_\epsilon = 0.555$

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data (2017)	0.327	0.343	0.092	0.166	0.364	4.01	0.043
Model (2017)	0.327	0.343	0.092	0.154	0.364	4.01	0.115

Table A.5.3: Understanding the changes between 1999 and 2017

	δ_1	δ_2	δ_3	h	$mjfr$	mvd	u
Data: Δ 1999-2017	-0.060	-0.040	-0.020	-0.049	-0.122	0.000	0.001
k_r	0.002	0.003	0.000	0.001	-0.046	-0.521	0.014
A	0.002	0.003	0.000	0.001	-0.042	0.324	0.013
λ	-0.007	-0.015	-0.021	-0.032	0.011	0.1388	-0.021
α	-0.032	0.002	0.003	-0.004	-0.010	0.049	0.001
σ_ϵ	-0.028	-0.035	-0.001	-0.016	-0.049	0.553	0.037