Online Appendices

"Does Working from Home Work? A Natural Experiment From Lockdowns"

(March 2022)

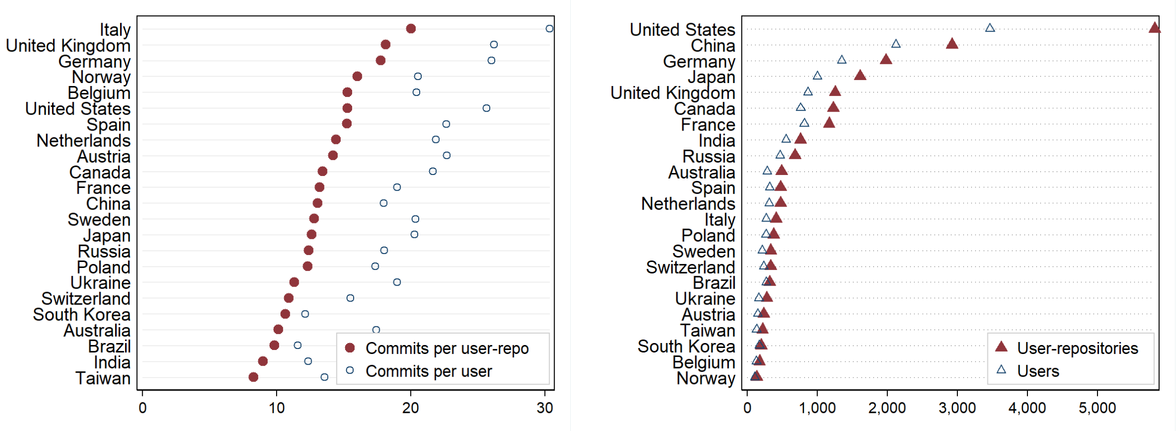


Figure A1: Largest countries in sample

Notes. Sample size by country, in descending order. Panel (a) sorts countries by number of commits per user-repository. Panel (b) sorts countries by number of user-repository.

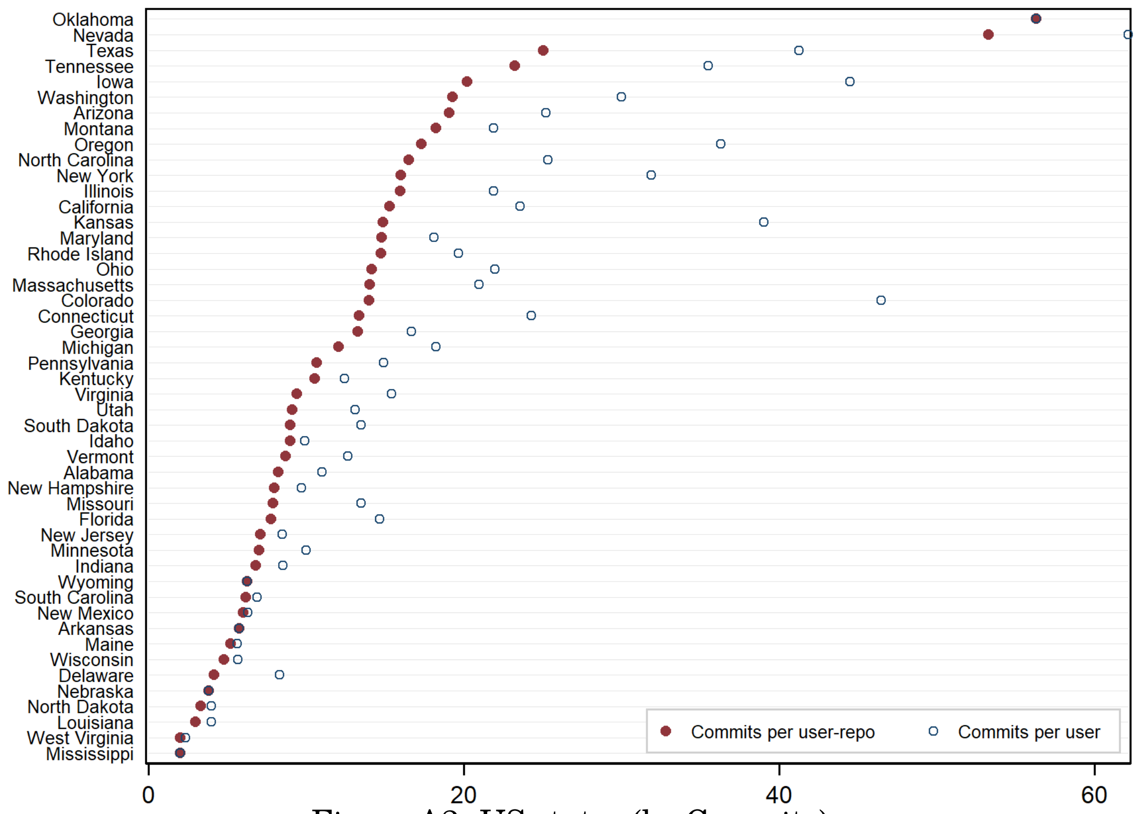


Figure A2: US states (by Commits)

Notes. US sample size by states, in descending order. States sorted by number of commits per user-repository.

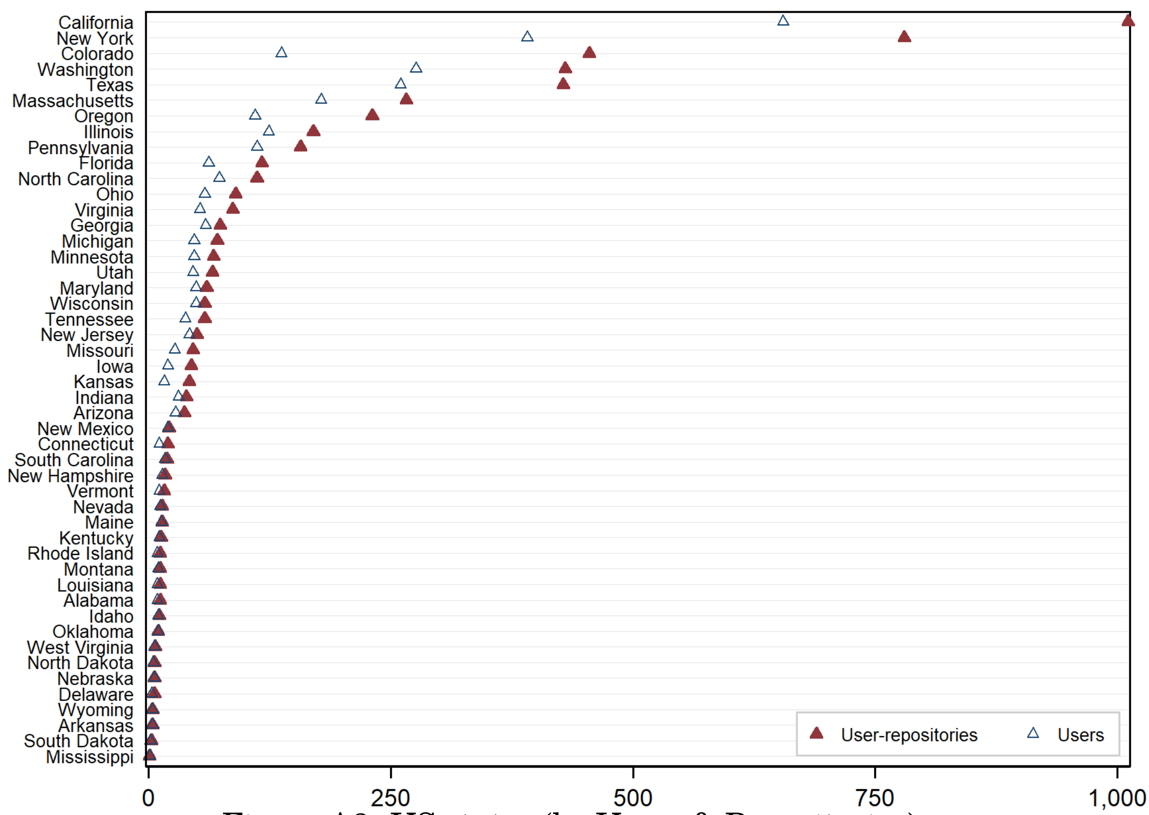
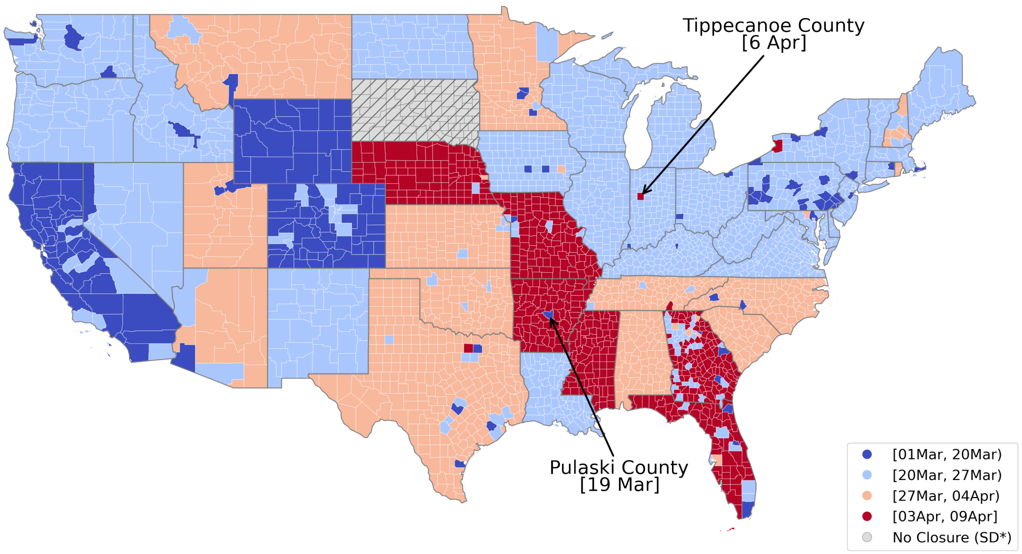
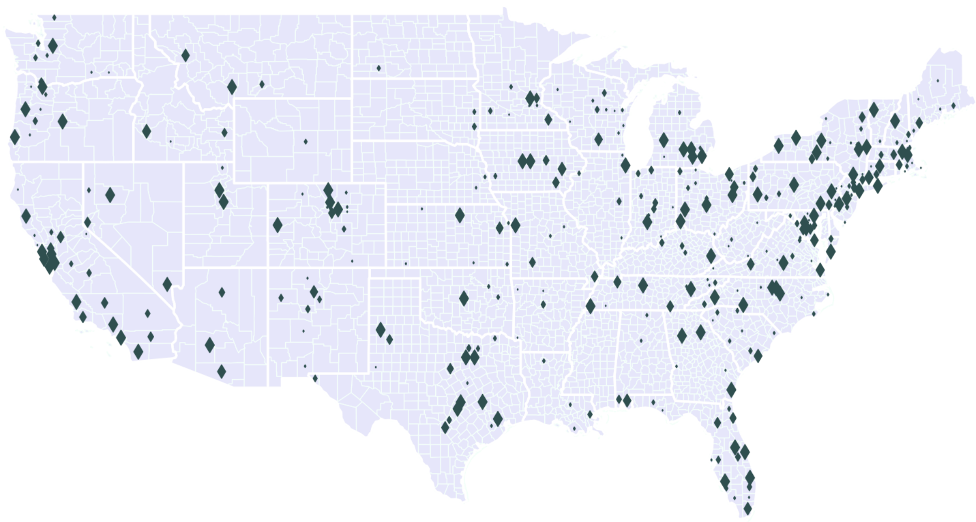


Figure A3: US states (by Users & Repositories)

Notes. US sample size by states, in descending order. States sorted by number user-repository.



(a) Staggered Timing in County-level Business Closures

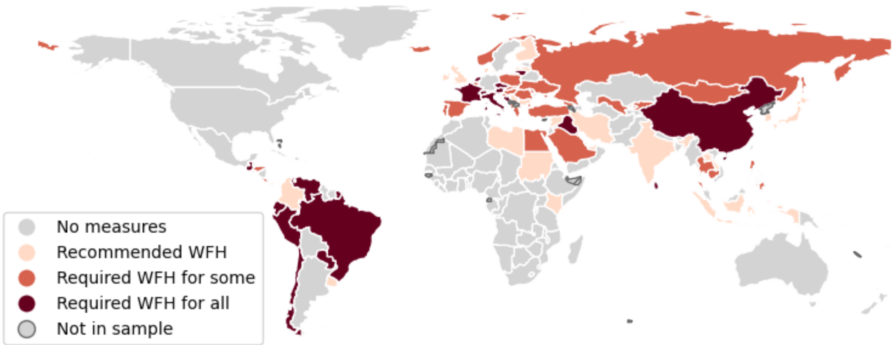


(b) County-level Variation in Sample Sizes

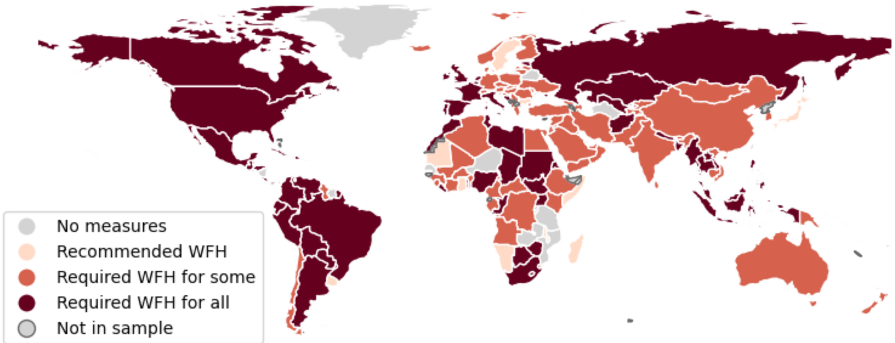
Figure A4: Geographical Variation in US sample

Notes—Panel (a) plots the county-level variation in business closures from the US-state level records and crowdsourced county-level records. Blue indicates earlier closures, while red indicates later closures. South Dakota is (still) the sole state without closure at the time of writing. Panel (b) plots the geographic variation of commits from geocoded U.S. users—larger markers indicate larger activity in the sample period.

(a) Early response (by 15 Feb)



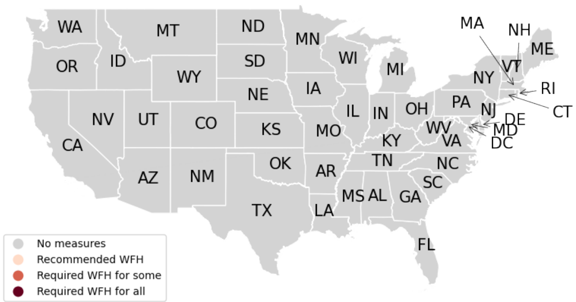
(b) Intermediate response (by 17 Mar)



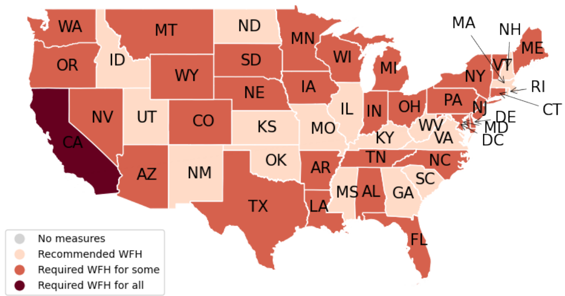
(c) Late response (by 30 Apr)

Figure A5: Country variation in WFH enforcement

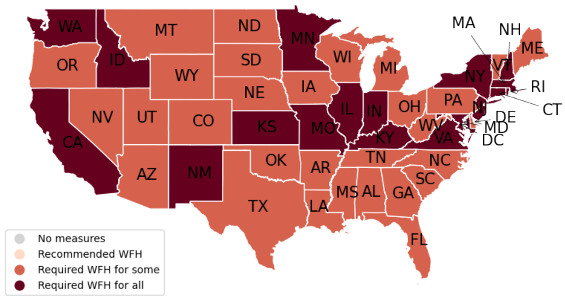
Notes. Figure plots the variation in government-enforced WFH levels during the COVID-19 pandemic. WFH indicators come from the OxCGRT (Petherick et al., 2020).



(a) Early response (by 15 Feb)



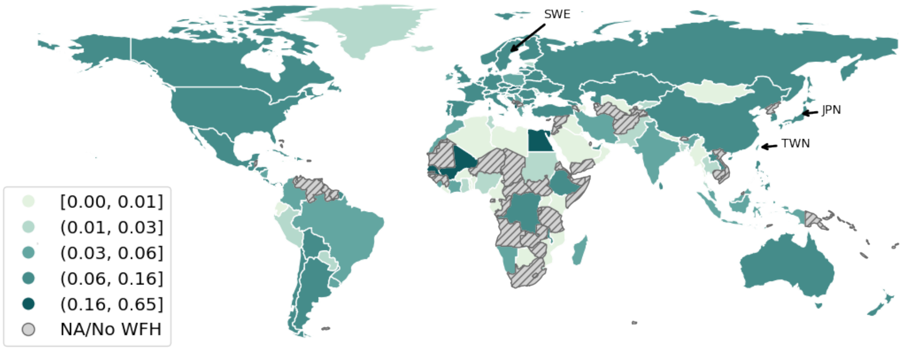
(b) Intermediate response (by 17 Mar)



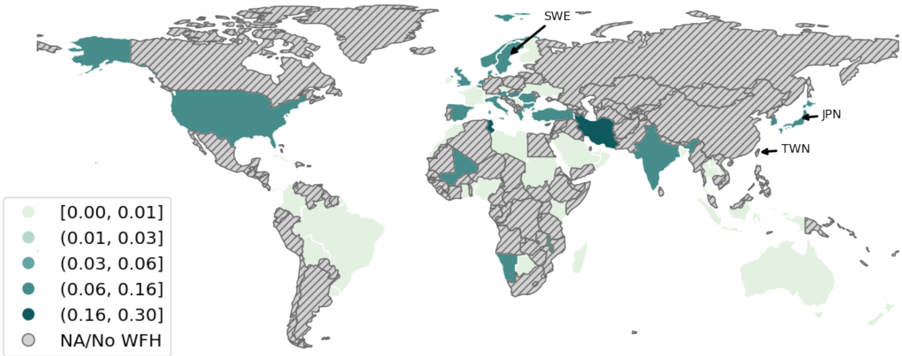
(c) Late response (by 30 Apr)

Figure A6: U.S. states variation in WFH enforcement

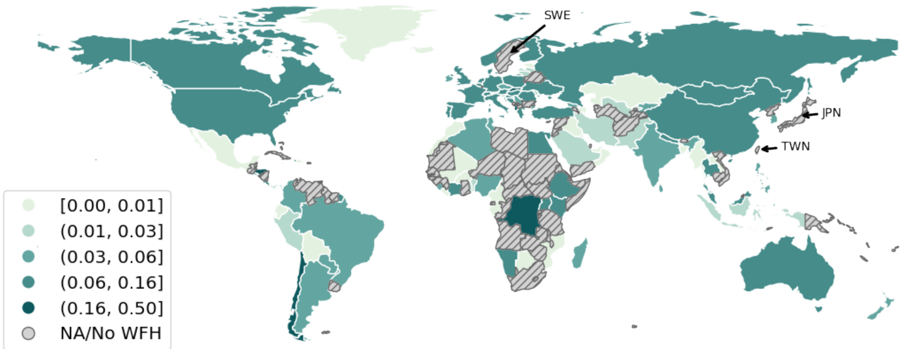
Notes. Figure plots the U.S. states variation in government-enforced WFH levels during the COVID-19 pandemic. WFH indicators come from the OxCGRT (Petherick et al., 2020).



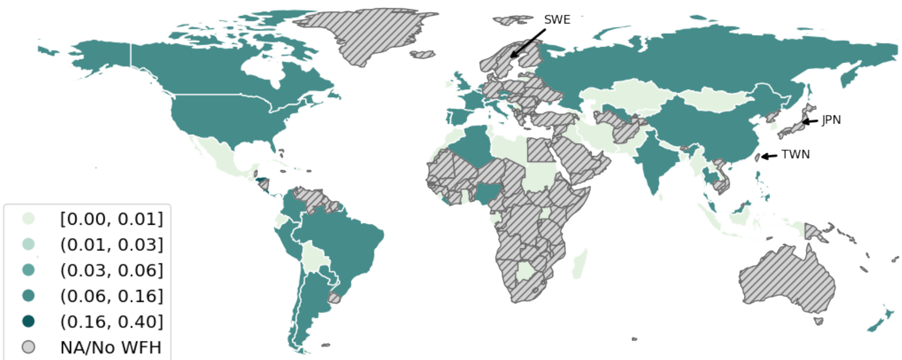
(a) Baseline (WFH = 0)



(b) Recommended WFH (WFH = 1)



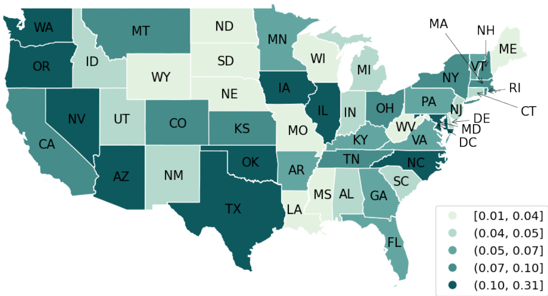
(c) Required WFH for some (WFH = 2)



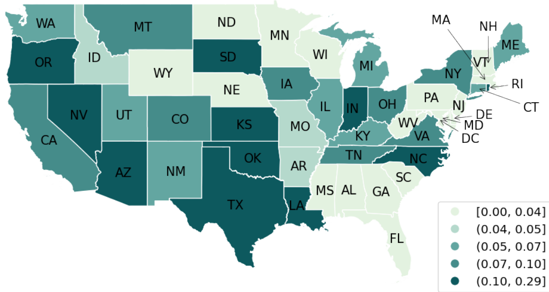
(d) Required WFH for all but essential (WFH = 3)

Figure A7: Country variation in activity, by WFH status

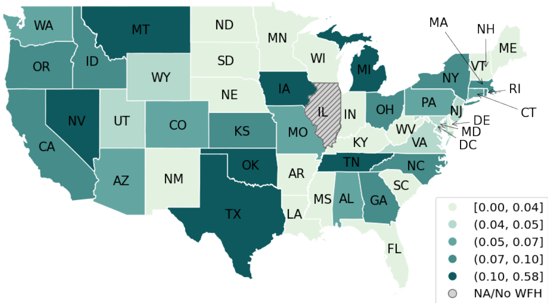
Notes. Figure plots the variation in activity level according to government-enforced WFH levels during the COVID-19 pandemic. These are from the commits per user-repo-day (for each given WFH period, total commits in that period divided by days in WFH period), aggregated up to the country-WFH level. Shaded areas indicate countries that do not have a particular WFH enforcement from Jan–Jun 2020. WFH indicators come from the OxCGRT (Petherick et al., 2020).



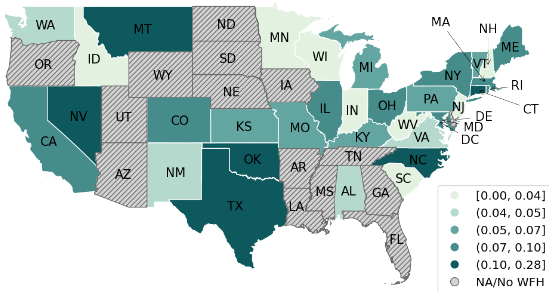
(a) Baseline (WFH = 0)



(b) Recommended WFH (WFH = 1)



(c) Required WFH for some (WFH = 2)



(d) Required WFH for all but some (WFH = 3)

Figure A8: U.S. states variation in activity, by WFH status

Notes. Figure plots the variation in activity level according to U.S. state-level government-enforced WFH levels during the COVID-19 pandemic. These are from the commits per user-repo-day (for each given WFH period, total commits in that period divided by days in WFH period), aggregated up to the state-WFH level. Shaded areas indicate state that do not have a particular WFH enforcement from Jan–Jun 2020. WFH indicators come from the OxCGRT (Petherick et al., 2020).

Table A1—*Language Distribution (Commits sample)*

language	No.	%
JavaScript	16,392	16.98
Python	13,200	13.68
Java	9,712	10.06
PHP	6,884	7.13
Go	5,952	6.17
C++	5,748	5.96
HTML	5,024	5.21
Ruby	4,128	4.28
TypeScript	3,588	3.72
C	3,516	3.64
Shell	3,224	3.34
CSS	2,972	3.08
C#	2,928	3.03
Scala	1,004	1.04
Jupyter Notebook	872	0.90
Rust	872	0.90
Swift	840	0.87
R	640	0.66
Vim script	620	0.64
Objective-C	596	0.62
Kotlin	536	0.56
Emacs Lisp	508	0.53
Perl	396	0.41
Dockerfile	392	0.41
Lua	376	0.39
Groovy	288	0.30
Clojure	272	0.28
Dart	272	0.28
PowerShell	272	0.28
MATLAB	260	0.27
TeX	248	0.26
Vue	248	0.26
Haskell	200	0.21
CoffeeScript	196	0.20
Erlang	184	0.19
Fortran	172	0.18
Elixir	168	0.17
TSQL	144	0.15
Julia	132	0.14
OCaml	116	0.12
Pascal	116	0.12
Assembly	108	0.11
Makefile	108	0.11
CMake	84	0.09
Visual Basic .NET	80	0.08
Starlark	76	0.08
Batchfile	72	0.07
F#	64	0.07
Nim	64	0.07
Vala	60	0.06
Smalltalk	56	0.06
ABAP	52	0.05
DM	52	0.05
Haxe	52	0.05
Crystal	48	0.05
PLpgSQL	48	0.05
Zig	48	0.05
D	40	0.04
Puppet	40	0.04
QML	40	0.04
XSLT	40	0.04
Common Lisp	36	0.04
Scheme	36	0.04
Vim Snippet	36	0.04
HCL	32	0.03
Jsonnet	32	0.03
VHDL	32	0.03
Elm	28	0.03
Roff	28	0.03

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Table A1 – *Continued from previous page*

Language	No.	%
Smarty	28	0.03
ActionScript	24	0.02
Ada	24	0.02
AutoHotkey	24	0.02
SourcePawn	24	0.02
Coq	20	0.02
Nix	20	0.02
Raku	20	0.02
Rich Text Format	20	0.02
SuperCollider	20	0.02
Markdown	16	0.02
OpenSCAD	16	0.02
PLSQL	16	0.02
Racket	16	0.02
Reason	16	0.02
Tcl	16	0.02
Verilog	16	0.02
ASP	12	0.01
BitBake	12	0.01
GLSL	12	0.01
Gherkin	12	0.01
IDL	12	0.01
Lasso	12	0.01
Mathematica	12	0.01
OpenEdge ABL	12	0.01
PureScript	12	0.01
RobotFramework	12	0.01
SQLPL	12	0.01
Stan	12	0.01
SystemVerilog	12	0.01
Apex	8	0.01
Cirru	8	0.01
ColdFusion	8	0.01
Cuda	8	0.01
HLSL	8	0.01
Hack	8	0.01
Isabelle	8	0.01
LiveScript	8	0.01
Logos	8	0.01
MQL5	8	0.01
MTML	8	0.01
Max	8	0.01
Objective-J	8	0.01
PostScript	8	0.01
Prolog	8	0.01
SWIG	8	0.01
Squirrel	8	0.01
YARA	8	0.01
YASnippet	8	0.01
sed	8	0.01
API Blueprint	4	0.00
AngelScript	4	0.00
ApacheConf	4	0.00
E	4	0.00
Factor	4	0.00
Forth	4	0.00
FreeMarker	4	0.00
G-code	4	0.00
GAMS	4	0.00
GAP	4	0.00
GDScript	4	0.00
Gnuplot	4	0.00
IGOR Pro	4	0.00
KiCad Layout	4	0.00
LLVM	4	0.00
LOLCODE	4	0.00
LabVIEW	4	0.00
Lex	4	0.00
Limbo	4	0.00

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Table A1 – *Continued from previous page*

Language	No.	%
M	4	0.00
Modelica	4	0.00
Modula-2	4	0.00
NewLisp	4	0.00
Nextflow	4	0.00
Objective-C++	4	0.00
P4	4	0.00
Pawn	4	0.00
Pony	4	0.00
Processing	4	0.00
PureBasic	4	0.00
Rebol	4	0.00
Riot	4	0.00
SMT	4	0.00
SQF	4	0.00
VBA	4	0.00
VBScript	4	0.00
VimL	4	0.00
Volt	4	0.00
XProc	4	0.00
ZenScript	4	0.00
q	4	0.00
Total	96,516	100.00

Table A2—*Language Distribution (Pull request sample)*

Language	No.	%
JavaScript	78,005	16.906
Python	72,598	15.734
PHP	36,556	7.923
Java	34,708	7.522
Go	33,132	7.181
Ruby	32,736	7.095
C++	21,104	4.574
TypeScript	19,395	4.203
C	15,636	3.389
C#	13,724	2.974
Shell	13,592	2.946
HTML	12,640	2.739
Rust	7,284	1.579
Swift	7,172	1.554
CSS	6,748	1.462
Scala	4,940	1.071
Kotlin	3,264	0.707
Objective-C	3,076	0.667
Elixir	2,816	0.610
Jupyter Notebook	2,756	0.597
Haskell	2,656	0.576
Dart	2,220	0.481
Julia	2,136	0.463
Dockerfile	2,104	0.456
Emacs Lisp	1,916	0.415
Perl	1,668	0.362
Vim script	1,616	0.350
Groovy	1,596	0.346
Clojure	1,592	0.345
Lua	1,284	0.278
PowerShell	1,248	0.270
Erlang	1,240	0.269
R	1,232	0.267
CoffeeScript	964	0.209
OCaml	920	0.199
Vue	916	0.199
Makefile	852	0.185
Starlark	740	0.160
Crystal	672	0.146
PureScript	628	0.136
F#	588	0.127
Puppet	580	0.126
TSQL	472	0.102
TeX	460	0.100
CMake	456	0.099
Jsonnet	420	0.091
Vala	400	0.087
MATLAB	368	0.080
BitBake	336	0.073
Common Lisp	336	0.073
Smalltalk	316	0.068
Fortran	292	0.063
Haxe	288	0.062
HCL	272	0.059
Nim	268	0.058
Nix	248	0.054
PLpgSQL	244	0.053
Elm	236	0.051
Smarty	232	0.050
Assembly	204	0.044
XSLT	176	0.038
Gherkin	164	0.036
D	160	0.035
Raku	160	0.035
Roff	148	0.032
Pascal	136	0.029
Reason	120	0.026
Rich Text Format	116	0.025
SourcePawn	104	0.023

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Table A2 – *Continued from previous page*

Language	No.	%
Apex	100	0.022
ColdFusion	96	0.021
Scheme	96	0.021
Visual Basic .NET	96	0.021
ABAP	80	0.017
QML	80	0.017
Batchfile	76	0.016
Tcl	72	0.016
Coq	68	0.015
Objective-C++	68	0.015
GDScript	64	0.014
Common Workflow Language	60	0.013
Cuda	60	0.013
Racket	60	0.013
VHDL	60	0.013
Prolog	56	0.012
SWIG	52	0.011
Agda	48	0.010
SaltStack	48	0.010
Vim Snippet	48	0.010
Zig	48	0.010
1C Enterprise	44	0.010
F*	44	0.010
Pawn	44	0.010
YASnippet	44	0.010
Lasso	40	0.009
Markdown	40	0.009
Perl 6	40	0.009
PLSQL	36	0.008
SystemVerilog	36	0.008
GAP	32	0.007
GLSL	32	0.007
Hack	32	0.007
IDL	32	0.007
M4	32	0.007
RobotFramework	32	0.007
SQF	32	0.007
Mathematica	28	0.006
Ada	24	0.005
Augeas	24	0.005
SuperCollider	24	0.005
Verilog	24	0.005
WebAssembly	24	0.005
q	24	0.005
AutoHotkey	20	0.004
Awk	20	0.004
FreeMarker	20	0.004
LookML	20	0.004
Nextflow	20	0.004
PostScript	20	0.004
Stan	20	0.004
VBA	20	0.004
YAML	20	0.004
YARA	20	0.004
Yacc	20	0.004
ANTLR	16	0.003
API Blueprint	16	0.003
Cirru	16	0.003
Dhall	16	0.003
Factor	16	0.003
OpenEdge ABL	16	0.003
P4	16	0.003
Pony	16	0.003
SQLPL	16	0.003
Visual Basic	16	0.003
Xtend	16	0.003
AutoIt	12	0.003
DIGITAL Command Language	12	0.003
DM	12	0.003

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Table A2 – *Continued from previous page*

Language	No.	%
Gnuplot	12	0.003
LilyPond	12	0.003
Logos	12	0.003
Stata	12	0.003
VimL	12	0.003
ASP	8	0.002
ActionScript	8	0.002
AppleScript	8	0.002
COBOL	8	0.002
EmberScript	8	0.002
Genshi	8	0.002
Hy	8	0.002
Idris	8	0.002
LiveScript	8	0.002
M	8	0.002
Mako	8	0.002
Max	8	0.002
Meson	8	0.002
Modelica	8	0.002
Open Policy Agent	8	0.002
Pan	8	0.002
RAML	8	0.002
Ragel in Ruby Host	8	0.002
SMT	8	0.002
Smali	8	0.002
Standard ML	8	0.002
Uno	8	0.002
UnrealScript	8	0.002
VBScript	8	0.002
Xojo	8	0.002
AGS Script	4	0.001
AngelScript	4	0.001
Bluespec	4	0.001
Brainfuck	4	0.001
CLIPS	4	0.001
CSON	4	0.001
Csound Document	4	0.001
Dylan	4	0.001
E	4	0.001
FORTRAN	4	0.001
Forth	4	0.001
G-code	4	0.001
GDB	4	0.001
Isabelle	4	0.001
Kit	4	0.001
LFE	4	0.001
LLVM	4	0.001
LOLCODE	4	0.001
LabVIEW	4	0.001
Lean	4	0.001
Lex	4	0.001
MQL5	4	0.001
NewLisp	4	0.001
ObjectScript	4	0.001
OpenSCAD	4	0.001
Perl6	4	0.001
Processing	4	0.001
Ragel	4	0.001
Ring	4	0.001
SAS	4	0.001
ShaderLab	4	0.001
XQuery	4	0.001
wdl	4	0.001
Total	461,406	100.000

A Differences in means

Table A3—*Characteristics of Users: Geocoded vs. Out of Sample (Commits Sample)*

Variable	(1) Geocoded Mean/SE	(2) Out of sample Mean/SE	(3) Total Mean/SE	T-test Difference (1)-(2)
User age ('00 days)	24.394	19.046	21.023	5.347***
	(0.410)	(0.000)	(1.321)	
Public repos	39.060	16.493	24.833	22.567***
	(2.146)	(0.000)	(5.596)	
Followers	69.352	13.582	34.192	55.770***
	(13.120)	(0.000)	(14.844)	
Following	23.229	4.840	11.636	18.389***
	(2.760)	(0.000)	(4.610)	
Gists	9.612	3.560	5.797	6.051***
	(1.418)	(0.000)	(1.567)	
$\mathbb{1}^{\text{Company listed}}$	0.498	0.072	0.230	0.426***
	(0.018)	(0.000)	(0.105)	
$\mathbb{1}^{\text{Organization}}$	0.007	0.009	0.008	-0.002
	(0.001)	(0.000)	(0.001)	
N	16591	28303	44894	
Clusters	139	1	140	

Notes: Table summarizes the user-level characteristics for the micro-sample originating from the commits log records. Columns (1)–(2) show the means for the geocoded sample used in the analyses and the out-of-geocoded sample (those not successfully geocoded). Column (3) shows the means for both combined. Column (4) shows the difference of column (1) and column (2). ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.

Table A4—*Characteristics of Users: Geocoded vs. Out of Sample (Pull Requests Sample)*

Variable	(1) Geocoded Mean/SE	(2) Out of sample Mean/SE	(3) Total Mean/SE	T-test Difference (1)-(2)
User age ('00 days)	23.561	17.051	20.815	6.510***
	(0.039)	(0.050)	(0.032)	
Public repos	44.250	23.914	35.673	20.337***
	(0.303)	(0.950)	(0.438)	
Followers	68.666	18.529	47.520	50.136***
	(2.469)	(1.463)	(1.557)	
Following	24.255	6.882	16.928	17.373***
	(0.635)	(0.215)	(0.379)	
Gists	15.688	3.806	10.676	11.882***
	(3.807)	(0.115)	(2.202)	
$\mathbb{1}^{\text{Company listed}}$	0.579	0.142	0.394	0.437***
	(0.002)	(0.002)	(0.001)	
$\mathbb{1}^{\text{Organization}}$	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	
N	69743	50871	120614	

Notes: Table summarizes the user-level characteristics for the micro-sample originating from the pull requests log records. Columns (1)–(2) show the means for the geocoded sample used in the analyses and the out-of-geocoded sample (those not successfully geocoded). Column (3) shows the means for both combined. Column (4) shows the difference of column (1) and column (2). ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.

Table A5—*Individual Characteristics, Commits Sample*

Variable	(1) No WFH Mean/SE	(2) RCMD WFH Mean/SE	(3) Required WFH Mean/SE	(4) Total Mean/SE	T-test Difference (1)-(2)	(1)-(3)
User age ('00 days)	23.950	24.000	23.811	23.893	-0.050	0.139**
	(0.445)	(0.838)	(0.464)	(0.482)		
Public repos	42.952	45.373	43.043	43.284	-2.421	-0.092
	(1.671)	(3.179)	(1.718)	(1.682)		
Followers	96.829	111.773	101.517	100.743	-14.944	-4.687
	(20.249)	(23.809)	(19.530)	(18.122)		
Following	27.647	29.545	28.660	28.333	-1.897	-1.013
	(5.234)	(5.767)	(5.108)	(4.823)		
Gists	11.262	12.189	10.971	11.242	-0.927	0.291*
	(1.546)	(1.503)	(1.397)	(1.427)		
$\mathbb{1}^{\text{Organization}}$	0.006	0.008	0.006	0.006	-0.002	0.000
	(0.001)	(0.003)	(0.001)	(0.001)		
$\mathbb{1}^{\text{Company listed}}$	0.544	0.577	0.542	0.547	-0.034**	0.002
	(0.020)	(0.014)	(0.019)	(0.019)		
N	4352	1221	4602	10175		
Clusters	89	39	89	89		

Notes: Summary of the commits micrsample for the three groups in columns (1)–(3): No WFH, recommended WFH, and required WFH (where OxCGRT's WFH coding = 2,3). Column (4) reports summary statistics for all. Columns (5)–(6) reports differences n means with No WFH as the baseline. N refers to the number of active individual-group cells recorded. Standard errors are clustered at the country level. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.

Table A6—*Repository Characteristics, Commits Sample*

Variable	(1) No WFH Mean/SE	(2) RCMD WFH Mean/SE	(3) Required WFH Mean/SE	(4) Total Mean/SE	T-test Difference (1)-(2)	(1)-(3)
Repo age ('00 days)	16.020	16.292	16.112	16.091	-0.272	-0.092
	(0.293)	(0.417)	(0.326)	(0.315)		
Contributors	13.201	15.353	12.910	13.277	-2.152***	0.291**
	(0.543)	(0.757)	(0.532)	(0.552)		
Contributions (by others, '00)	19.950	32.854	18.784	20.681	-12.903***	1.167**
	(2.119)	(5.218)	(2.087)	(2.352)		
$\mathbb{1}^{\text{Forked}}$	0.045	0.060	0.045	0.047	-0.015**	-0.001
	(0.005)	(0.009)	(0.006)	(0.006)		
Stars ('00)	11.990	15.028	10.800	11.726	-3.038	1.190***
	(1.640)	(2.847)	(1.502)	(1.629)		
Forks	311.180	481.560	291.373	318.731	-170.379**	19.807*
	(37.121)	(111.836)	(37.338)	(42.859)		
Open issues	60.870	92.325	56.329	61.842	-31.456***	4.541***
	(7.560)	(13.924)	(7.377)	(8.019)		
N	6324	1487	7105	14916		
Clusters	117	72	118	128		

Notes: Summary of the commits micrsample for the three groups in columns (1)–(3): No WFH, recommended WFH, and required WFH (where OxCGRT's WFH coding = 2,3). Column (4) reports summary statistics for all. Columns (5)–(6) reports differences n means with No WFH as the baseline. N refers to the number of active repository-group cells recorded. Standard errors are clustered by programming language. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.

Table A7—*Individual Characteristics, Pulls Sample*

Variable	(1) No WFH Mean/SE	(2) RCMD WFH Mean/SE	(3) Required WFH Mean/SE	(4) Total Mean/SE	T-test Difference (1)-(2)	(1)-(3)
User age ('00 days)	26.369	25.667	26.111	26.146	0.702	0.257*
	(0.402)	(0.784)	(0.486)	(0.486)		
Public repos	66.313	64.607	63.849	64.916	1.706	2.464***
	(1.558)	(2.274)	(1.529)	(1.520)		
Followers	127.770	108.399	121.830	122.156	19.371*	5.939**
	(13.108)	(9.509)	(12.224)	(11.669)		
Following	34.449	27.032	32.850	32.613	7.417**	1.600***
	(3.098)	(1.087)	(2.846)	(2.639)		
Gists	20.872	23.248	21.354	21.446	-2.376	-0.482
	(2.540)	(5.178)	(2.893)	(2.798)		
$\mathbb{1}^{\text{Organization}}$	0.000	0.000	0.000	0.000	N/A	N/A
	(0.000)	(0.000)	(0.000)	(0.000)		
$\mathbb{1}^{\text{Company listed}}$	0.662	0.654	0.656	0.658	0.009	0.006*
	(0.017)	(0.021)	(0.016)	(0.016)		
N	9085	3449	10886	23420		
Clusters	98	56	102	102		

Notes: Summary of the pull requests microsample for the three groups in columns (1)–(3): No WFH, recommended WFH, and required WFH (where OxCGRT's WFH coding = 2,3). Column (4) reports summary statistics for all. Columns (5)–(6) reports differences n means with No WFH as the baseline. N refers to the number of active individual-group cells recorded. Standard errors are clustered at the country level. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.

Table A8—*Repository Characteristics, Pulls Sample*

Variable	(1) No WFH Mean/SE	(2) RCMD WFH Mean/SE	(3) Required WFH Mean/SE	(4) Total Mean/SE	T-test Difference (1)-(2)	(1)-(3)
Repo age ('00 days)	17.389	17.735	17.485	17.487	-0.346***	-0.096*
	(0.486)	(0.521)	(0.482)	(0.487)		
Contributors	15.449	18.402	16.623	16.459	-2.953***	-1.174***
	(0.268)	(0.333)	(0.288)	(0.273)		
Contributions (by others, '00)	6.917	12.378	9.624	9.059	-5.461***	-2.707***
	(0.655)	(1.137)	(0.698)	(0.725)		
$\mathbb{1}^{\text{Forked}}$	0.029	0.020	0.025	0.026	0.009***	0.004***
	(0.003)	(0.003)	(0.003)	(0.003)		
Stars ('00)	6.904	12.877	10.640	9.642	-5.973***	-3.735***
	(1.079)	(1.856)	(1.671)	(1.480)		
Forks	124.361	255.583	210.517	186.587	-131.223***	-86.156***
	(11.886)	(30.995)	(23.527)	(20.061)		
Open issues	26.543	52.212	40.974	37.480	-25.668***	-14.430***
	(1.711)	(3.811)	(3.075)	(2.657)		
N	13073	5195	19016	37284		
Clusters	124	96	139	152		

Notes: Summary of the pull requests microsample for the three groups in columns (1)–(3): No WFH, recommended WFH, and required WFH (where OxCGRT's WFH coding = 2,3). Column (4) reports summary statistics for all. Columns (5)–(6) reports differences n means with No WFH as the baseline. N refers to the number of active repository-group cells recorded. Standard errors are clustered by programming language. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.

Table A9—*US vs Rest of World*
Individual Characteristics From Commits Sample

Variable	(1) US Mean/SE	(2) Rest of world Mean/SE	(3) Total Mean/SE	T-test Difference (1)-(2)
User age ('00 days)	25.677	24.103	24.417	1.574***
	(0.000)	(0.411)	(0.424)	
Public repos	38.376	39.113	38.966	-0.737
	(0.000)	(2.728)	(2.199)	
Followers	75.611	69.046	70.355	6.565
	(0.000)	(16.953)	(13.494)	
Following	19.829	24.296	23.406	-4.467
	(0.000)	(3.220)	(2.749)	
Gists	11.303	9.188	9.610	2.115
	(0.000)	(1.761)	(1.461)	
$\mathbb{1}^{\text{Organization}}$	0.010	0.006	0.007	0.004***
	(0.000)	(0.001)	(0.001)	
$\mathbb{1}^{\text{Company listed}}$	0.569	0.481	0.499	0.088***
	(0.000)	(0.016)	(0.019)	
N	3194	12829	16023	
Clusters	1	124	125	

Notes: Table summarizes the individual characteristics for US-mapped observations vs the rest of the world, for observations in the commits micro-sample. Columns (1), (2), & (3) reports summary statistics for the US sample, rest of world, and both combined, respectively. Column (4) shows the difference of US vs rest of world. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.

Table A10—*US vs Rest of World*
Repository Characteristics From Commits Sample

Variable	(1) US Mean/SE	(2) Rest of world Mean/SE	(3) Total Mean/SE	T-test Difference (1)-(2)
Repo age ('00 days)	15.779	15.602	15.641	0.177
	(0.408)	(0.300)	(0.317)	
Contributors ('00)	11.613	11.508	11.531	0.105
	(0.584)	(0.484)	(0.485)	
Contributions (by others, '00)	12.314	12.101	12.147	0.213
	(1.886)	(1.152)	(1.256)	
$\mathbb{1}^{\text{Forked}}$	0.049	0.044	0.045	0.005
	(0.008)	(0.005)	(0.005)	
Stars ('00)	8.331	9.190	9.004	-0.859
	(1.251)	(1.306)	(1.193)	
Forks	204.346	220.482	216.983	-16.135
	(37.333)	(23.247)	(23.077)	
Open issues	38.990	38.857	38.886	0.133
	(4.913)	(3.982)	(4.060)	
N	4011	14488	18499	
Clusters	94	147	161	

Notes: Table summarizes the repository characteristics for US-mapped observations vs the rest of the world, for observations in the commits micro-sample. Columns (1), (2), & (3) reports summary statistics for the US sample, rest of world, and both combined, respectively. Column (4) shows the difference of US vs rest of world. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.

Table A11—*US vs Rest of World*
Individual Characteristics From Pulls Sample

Variable	(1) US Mean/SE	(2) Rest of world Mean/SE	(3) Total Mean/SE	T-test Difference (1)-(2)
User age ('00 days)	25.312	23.413	23.929	1.898***
	(0.000)	(0.534)	(0.536)	
Public repos	48.586	43.976	45.228	4.610***
	(0.000)	(1.404)	(1.373)	
Followers	98.597	61.505	71.577	37.093***
	(0.000)	(6.433)	(8.637)	
Following	21.634	25.248	24.266	-3.613**
	(0.000)	(1.796)	(1.498)	
Gists	15.285	16.959	16.505	-1.674
	(0.000)	(6.376)	(4.654)	
$\mathbb{1}^{\text{Organization}}$	0.000	0.000	0.000	-0.000**
	(0.000)	(0.000)	(0.000)	
$\mathbb{1}^{\text{Company listed}}$	0.637	0.563	0.583	0.075***
	(0.000)	(0.010)	(0.017)	
N	17116	45914	63030	
Clusters	1	143	144	

Notes: Table summarizes the individual characteristics for US-mapped observations vs the rest of the world, for observations in the pull requests micro-sample. Columns (1), (2), & (3) reports summary statistics for the US sample, rest of world, and both combined, respectively. Column (4) shows the difference of US vs rest of world. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.

Table A12—*US vs Rest of World*
Individual Characteristics From Repository Sample

Variable	(1) US Mean/SE	(2) Rest of world Mean/SE	(3) Total Mean/SE	T-test Difference (1)-(2)
Repo age ('00 days)	16.763	16.953	16.899	-0.190
	(0.484)	(0.370)	(0.399)	
Contributors ('00)	14.657	13.724	13.990	0.933***
	(0.302)	(0.188)	(0.206)	
Contributions (by others, '00)	10.543	7.292	8.219	3.251***
	(0.909)	(0.784)	(0.780)	
$\mathbb{1}^{\text{Forked}}$	0.030	0.030	0.030	-0.000
	(0.003)	(0.003)	(0.003)	
Stars ('00)	10.661	7.601	8.474	3.061***
	(1.288)	(1.050)	(1.079)	
Forks	247.145	148.990	176.995	98.155***
	(23.048)	(14.227)	(15.438)	
Open issues	48.670	29.412	34.906	19.258***
	(4.941)	(2.109)	(2.615)	
N	14242	35675	49917	
Clusters	135	179	200	

Notes: Table summarizes the repository-level characteristics for the micro-sample originating from the pull requests log records. Columns (1)–(2) show the means for the geocoded sample used in the analyses and the out-of-geocoded sample (those not successfully geocoded). Column (3) shows the means for both combined. Column (4) shows the difference of column (1) and column (2). ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.

B Time-of-day cadence

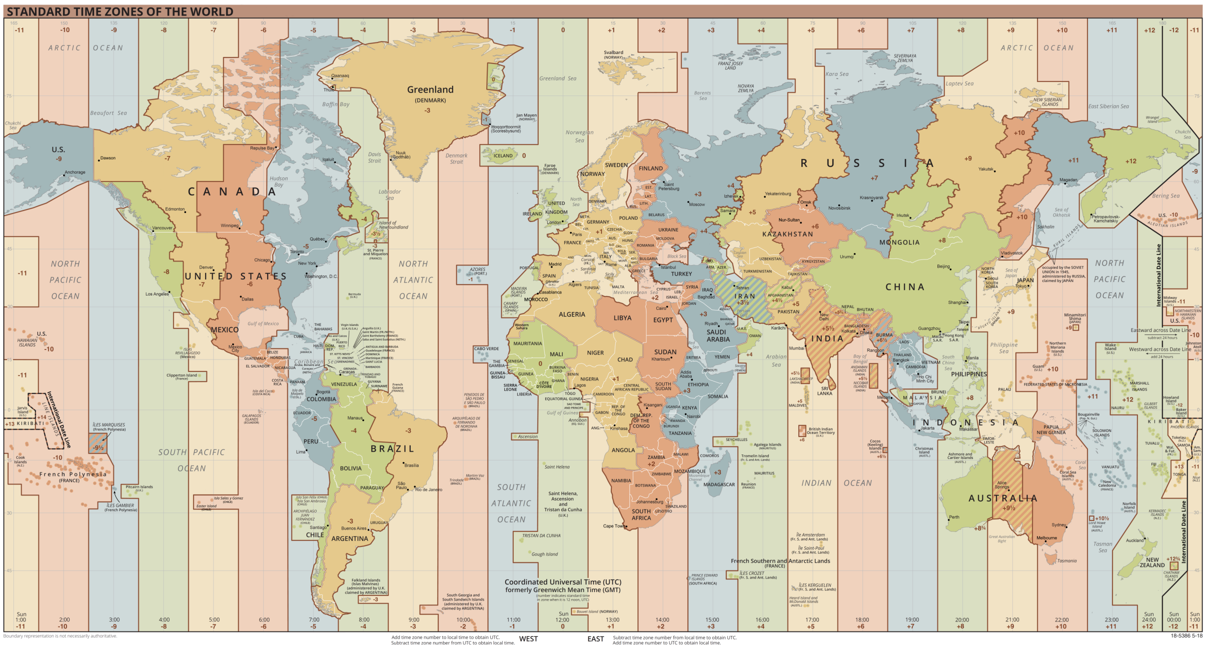


Figure A9: Timezones Across the Globe

Notes—Map of the world's timezones based on geo-coordinates. Image taken directly from https://en.wikipedia.org/wiki/Time_zone.

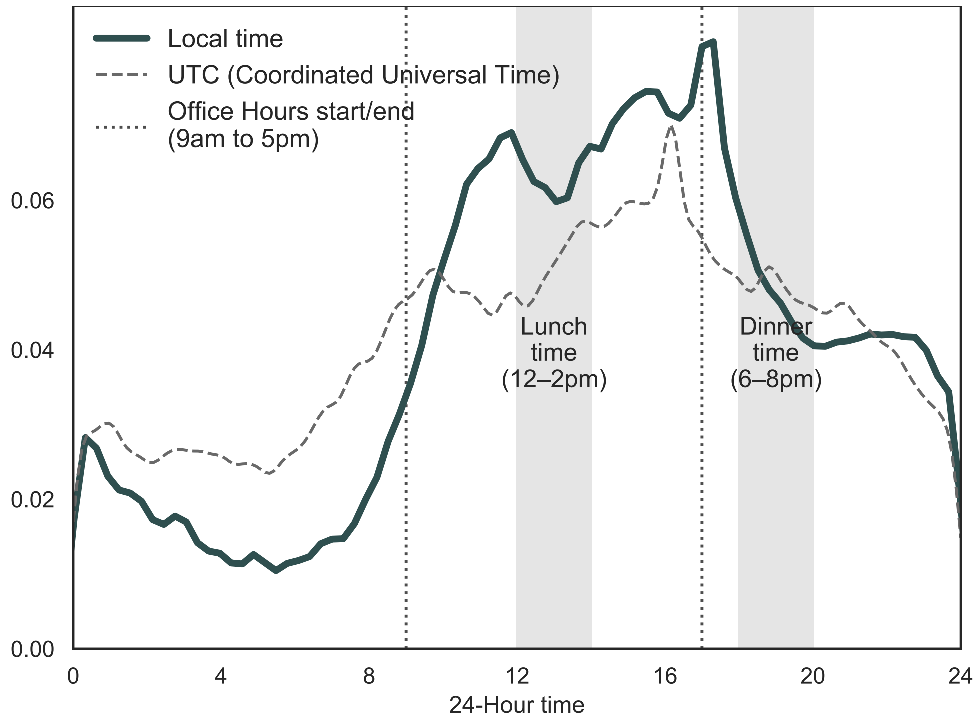


Figure A10: Time-of-Day cadence (Commits for those with companies)

Notes—Kerndel density estimate plot of the time-of-day-based cadence of the timestamped commits in 24-hour time. Only commits from users who are successfully geocoded and who have the companies they work at reported are included. Minimal smoothing applied. Solid thick line is local time (UTC offset ± hh based on inferred local timezone). Thin gray dashed line is the timezone-agnostic timestamp from the commits records. The two vertical dotted lines are the start and end time of "office hours" (9am to 5pm). The two gray shaded areas indicate the two standard meal times (noon to 2pm for lunch time; 6pm to 8pm for dinner time).

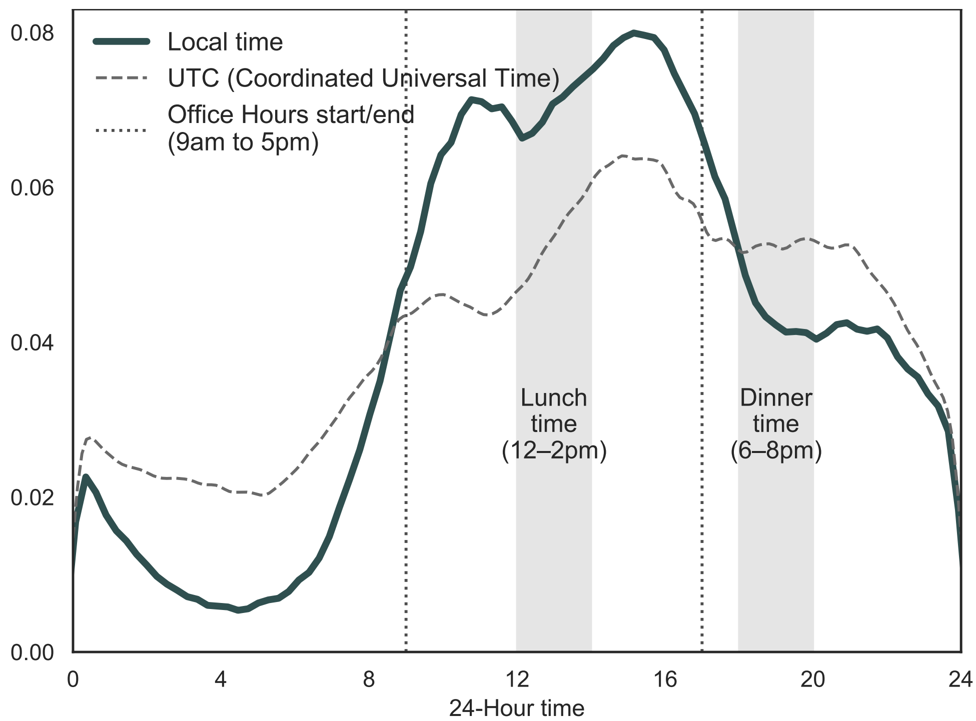


Figure A11: Time-of-Day cadence (Pull requests)

Notes—Kerndel density estimate plot of the time-of-day-based cadence of the timestamped commits in 24-hour time. Only commits from users who are successfully geocoded are included. Weighted by the number of commits observed in the Jan–Jun 2020 sample period. Minimal smoothing applied. Solid thick line is local time (UTC offset ± hh based on inferred local timezone). Thin gray dashed line is the timezone-agnostic timestamp from the commits records. The two vertical dotted lines are the start and end time of "office hours" (9am to 5pm). The two gray shaded areas indicate the two standard meal times (noon to 2pm for lunch time; 6pm to 8pm for dinner time).

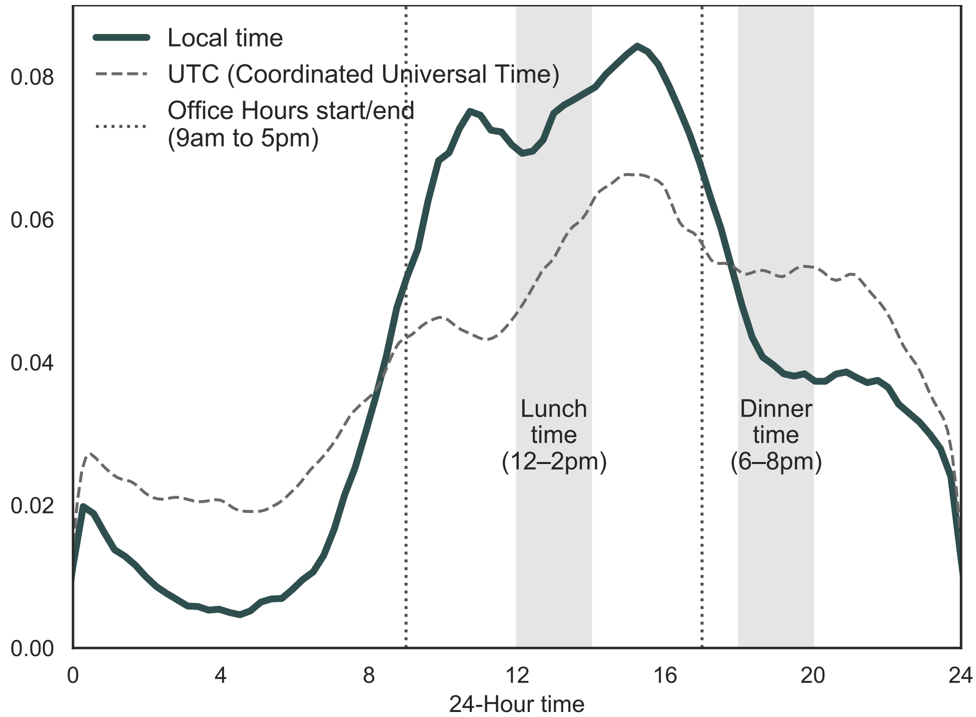


Figure A12: Time-of-Day cadence (Pull requests for those with companies)

Notes—Kerndel density estimate plot of the time-of-day-based cadence of the timestamped commits in 24-hour time. Only commits from users who are successfully geocoded and who have the companies they work at reported are included. Minimal smoothing applied. Solid thick line is local time (UTC offset ± hh based on inferred local timezone). Thin gray dashed line is the timezone-agnostic timestamp from the commits records. The two vertical dotted lines are the start and end time of "office hours" (9am to 5pm). The two gray shaded areas indicate the two standard meal times (noon to 2pm for lunch time; 6pm to 8pm for dinner time).

C Benchmarking

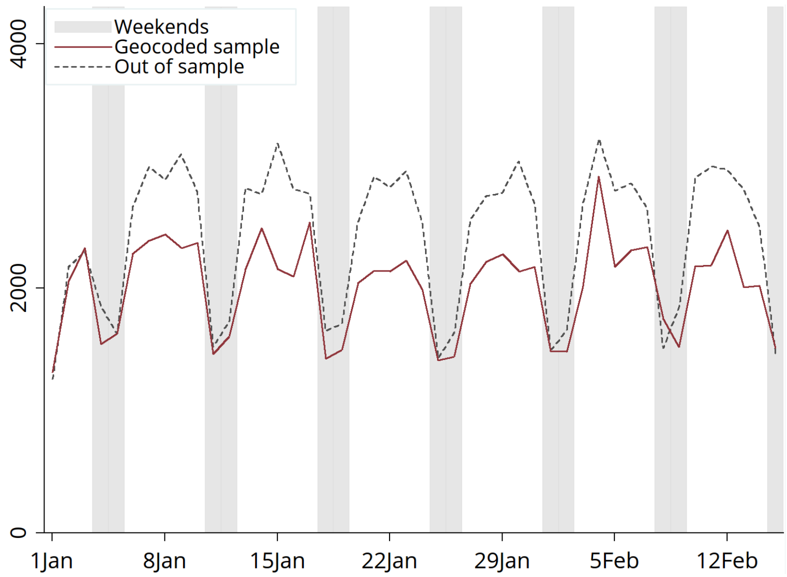
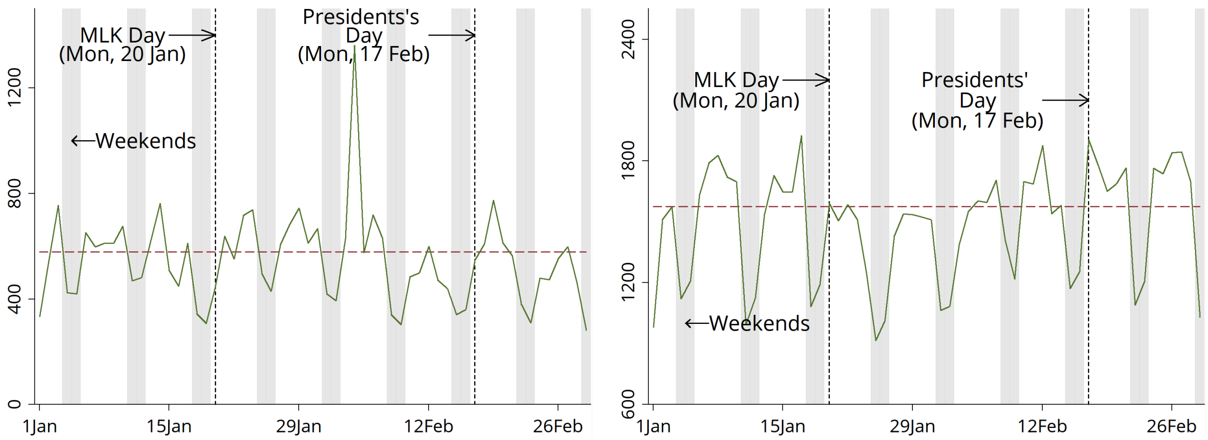


Figure A13: Commits in January 2020.

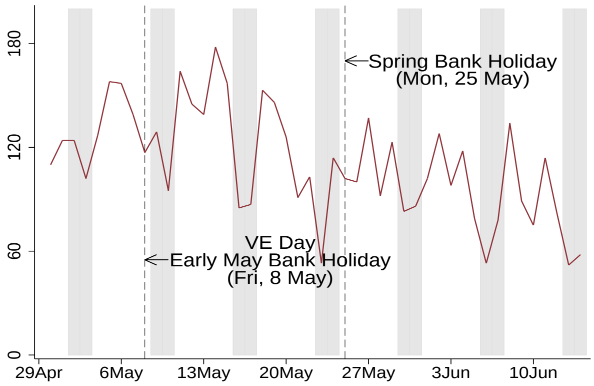
Notes. Path plot (unsmoothed) of commits in January 2020. Red solid line is the activity level of users that are successfully geocoded to a country or U.S. state; Black dotted line is the activity level of users that cannot be geocoded. Gray vertical bars indicate weekends (Sat–Sun).



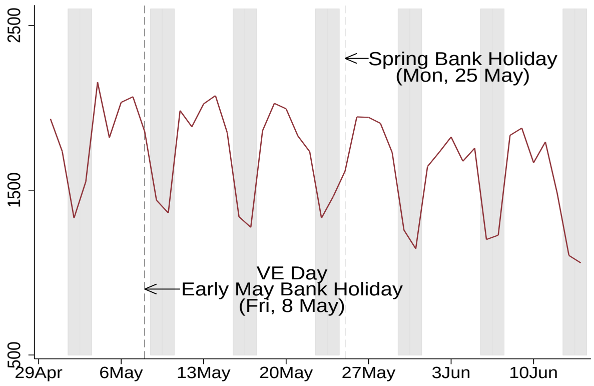
(a) U.S. sample (b) Non-U.S. sample

Figure A14: MLK Day (U.S. sample vs. others)

Notes. Path plot (unsmoothed) of commits around Jan–Feb 2020 for U.S. sample vs. others. First black dashed line indicates Martin Luther King Jr. Day on 20 Jan; second one indicates Washington's Birthday on 17 Feb. Both occur on Mondays. Horizontal lines show the Monday average over the shown sample period, excluding the two Monday holidays. Gray vertical bars indicate weekends (Sat–Sun).



(a) UK sample



(b) Non-UK sample

Figure A15: May Bank Holidays (UK sample vs. others)

Notes. Path plot (unsmoothed) of commits around May 2020 for U.K. sample vs. others. First black dashed line indicates Early May Bank Holiday on 8 May, which has been brought back to coincide with the Victory in Europe Day; second black dashed line one indicates the Spring Bank Holiday on 25 May. Gray vertical bars indicate weekends (Sat–Sun).

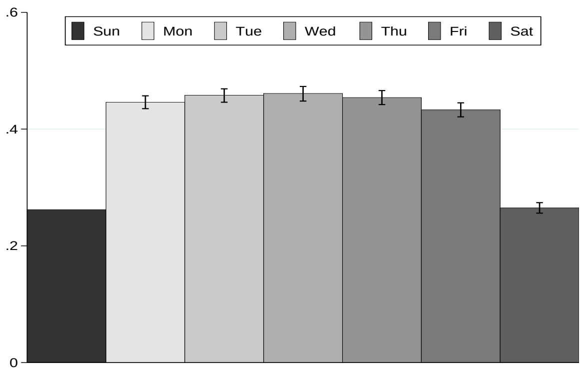
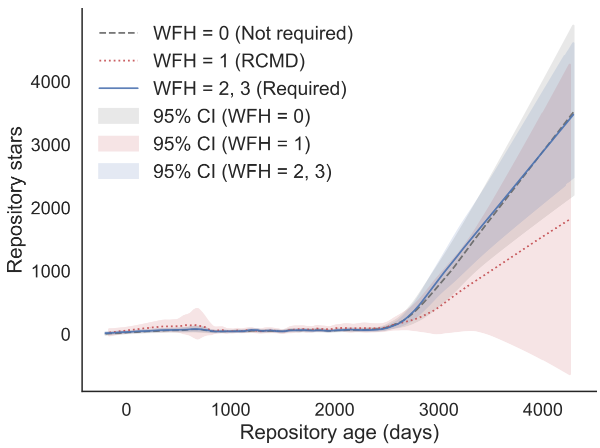
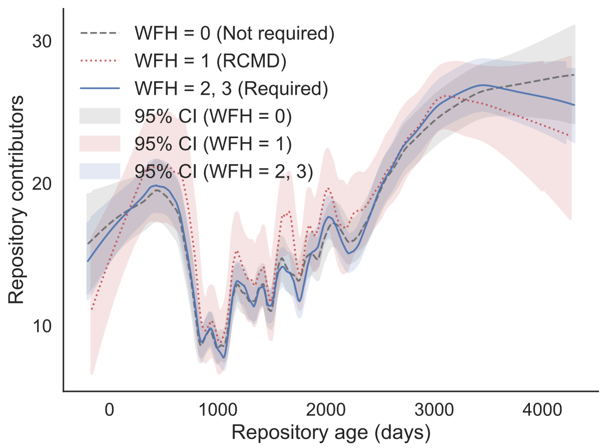


Figure A16: Day-of-Week Cadence (Out-of-Geocoded Sample) *Notes*—Bar plots show the differences in log of (1+) commits by day-of-week (DoW) from regressing commits on the day-of-week dummies, plus user and repository fixed effects for the user-repository-DoW panel. The baseline day is Sunday—first bar—so that the standard errors for subsequent bars are for the estimates of the additional effects of Mon–Sat relative to Sunday. Robust standard errors are clustered at users and repositories.



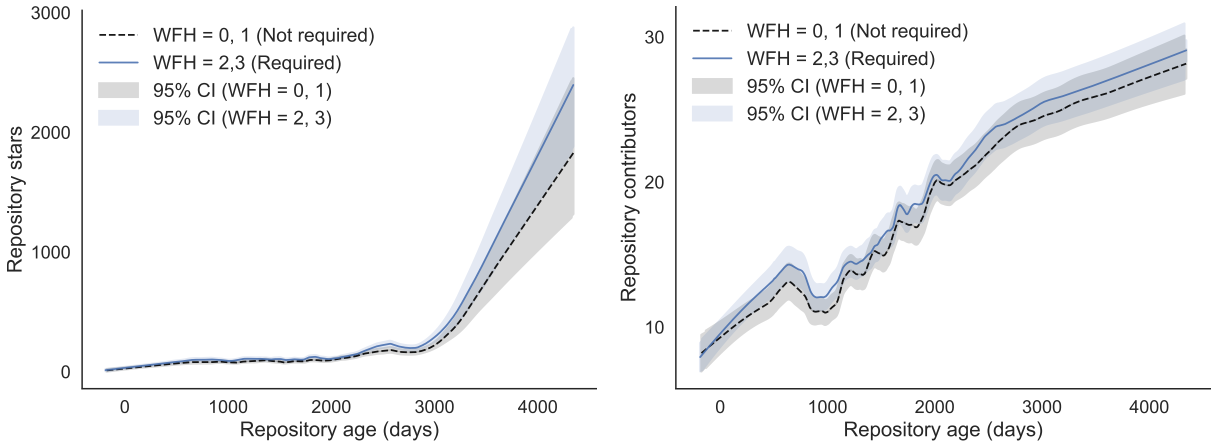
(a) Stars



(b) Contributors

Figure A17: Metrics of Quality and Size (Commits Sample)

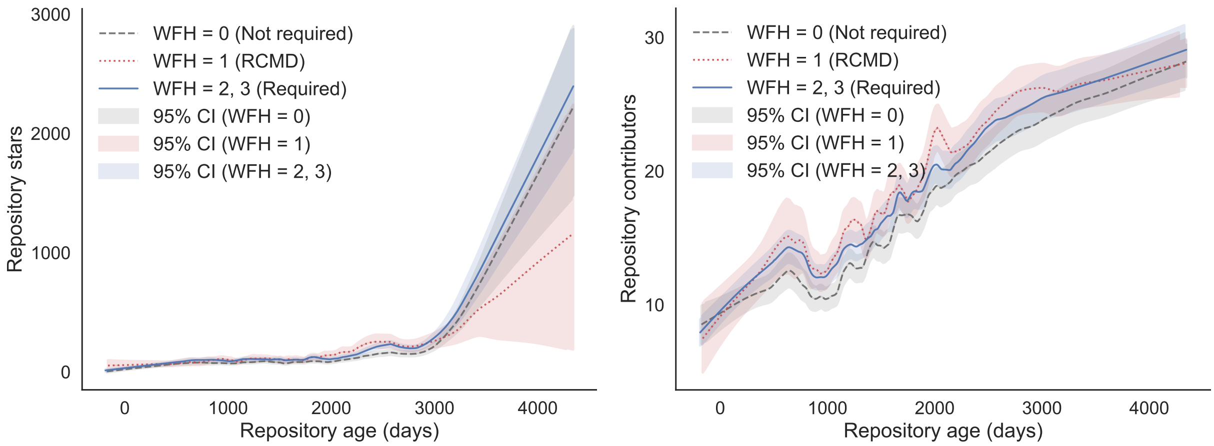
Notes—Blue solid line is repositories active during required WFH period. Pink dotted line is repositories in the recommended WFH period. Black dashed line is repositories outside of the required WFH period. Lines are from a locally weighted smoothing with minimal smoothing. Repository age is defined by the repository creation date relative to Jan 1, 2020. Shaded area indicates the bootstrapped 95% confidence interval (n=1,000).



(a) Stars (b) Contributors

Figure A18: Metrics of Quality and Size (Pull Requests Sample)

Notes—Blue solid line is repositories active during required WFH period. Black dashed line is repositories outside of the required WFH period. Lines are from a locally weighted smoothing with minimal smoothing. Repository age is defined by the repository creation date relative to Jan 1, 2020. Shaded area indicates the bootstrapped 95% confidence interval (n=1,000).



(a) Stars (b) Contributors

Figure A19: Metrics of Quality and Size (Pull Requests Sample)

Notes—Blue solid line is repositories active during required WFH period. Pink dotted line is repositories in the recommended WFH period. Black dashed line is repositories outside of the required WFH period. Lines are from a locally weighted smoothing with minimal smoothing. Repository age is defined by the repository creation date relative to Jan 1, 2020. Shaded area indicates the bootstrapped 95% confidence interval (n=1,000).

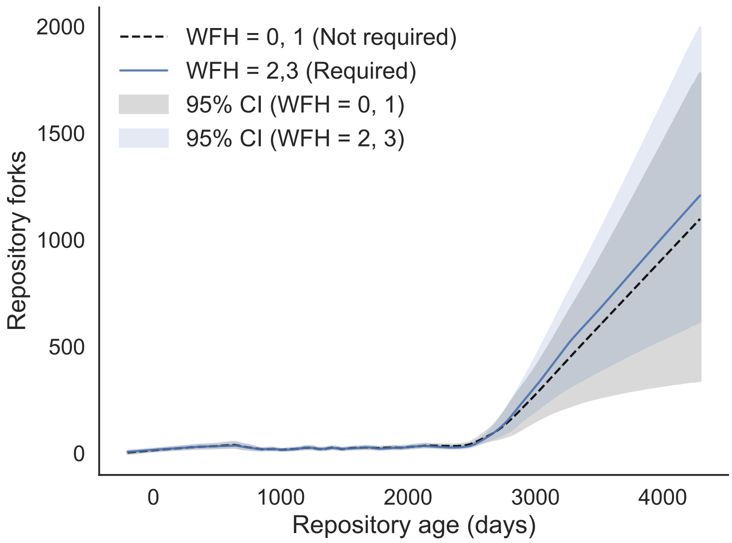


Figure A20: Forks (Commits Sample)

Notes—The alternative metric of quality is the number of forks (users who take the original project and use it as a basis for their own project). Blue solid line is repositories active during required WFH period. Black dashed line is repositories outside of the required WFH period. Lines are from a locally weighted smoothing with minimal smoothing. Repository age is defined by the repository creation date relative to Jan 1, 2020. Shaded area indicates the bootstrapped 95% confidence interval (n=1,000).

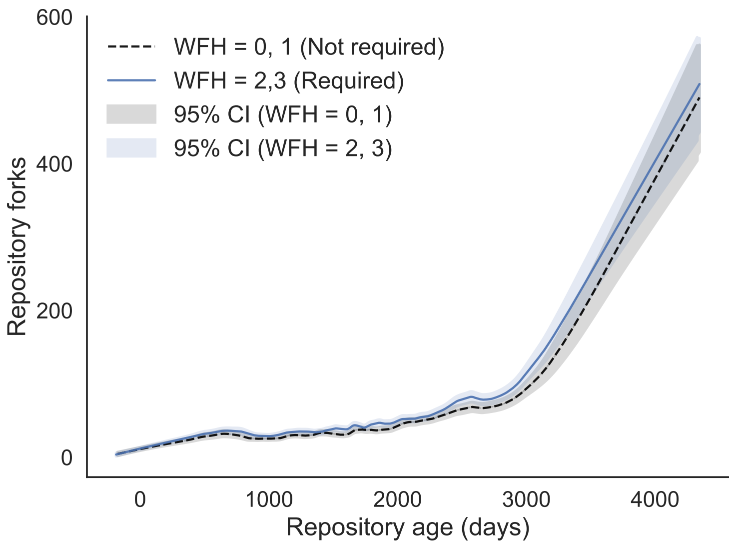


Figure A21: Forks (Pull Requests Sample)

Notes—The alternative metric of quality is the number of forks (users who take the original project and use it as a basis for their own project). Blue solid line is repositories active during required WFH period. Black dashed line is repositories outside of the required WFH period. Lines are from a locally weighted smoothing with minimal smoothing. Repository age is defined by the repository creation date relative to Jan 1, 2020. Shaded area indicates the bootstrapped 95% confidence interval (n=1,000).

D Event studies

Figure A27 shows the changes in productive output—commits and pull requests per user per day (all in logs)—from estimating a flexible event-study specification:[1]

$$y_{ct} = \alpha_c + \alpha_t + \boldsymbol{\beta}_t \boldsymbol{X}_{ct} + \sum_{\tau=-21}^{-2} \gamma_\tau \mathbb{1}_{\{t=T_c+\tau\}} + \sum_{\tau=0}^{21} \delta_\tau \mathbb{1}_{\{t=T_c+\tau\}} + \varepsilon_{ct}, \tag{1}$$

for a 21-day window before and after T_c, where T_c is Day 0 for country c—the date when the OxCGRT WFH indicator first switches to state-imposed WFH. Endpoints are binned and the day before T_c ($\tau = -1$) is the baseline. α_c and α_t are country and date fixed effects. $\boldsymbol{X}_{ct}$ includes cohort group-by-week-of-year fixed effects (Goodman-Bacon 2019), where a group is defined by the Day 0 timing. $\boldsymbol{X}_{ct}$ also includes two OxCGRT indices on government response,[2] and the COVID-19 epidemiology path (log of confirmed cases, recovered cases, deaths) because they potentially affect treatment anticipation in this particular context, with both sets allowed to have heterogeneous effects over time.

Conditional on the observables and the group-by-week linear time trends, estimates of γ_τ constitute conditional falsification tests for pretrends, and the δ_τ estimates trace out the daily effects of WFH on the work patterns. Standard errors are clustered by country.[3]

Figure A27 plots the estimates of γ_τ and δ_τ from Equation (1). Though measurement error will attenuate estimates substantially, I note distinct changes starting from Day 0. For commits, the estimated δ_{21} is .472 ($p < .047$), which is a 60 percent increase by day 21,[4] while the estimate for number of active individuals is .203 ($p < .156$), suggesting a 23 percent increase in the number of active individuals.[5] Overall, commits per user increased by 31 percent ($p < .048$).[6]

For pull requests, by day 21, I note a 31 percent increase in total pull requests per day ($p < .054$),[7] and a correspondingly large 31 increase in active individuals (p

[1] To accomodate zero records for the country-date cells, the commits per user measure is $\left[\right.$log(1 + commits) - log(1 + active commit users)$\left.\right]$, and similarly the pull requests per user measure is $\left[\right.$log(1 + pull requests) - log(1 + active pull users)$\left.\right]$.

[2] The "Government Response Index" and the "Economics Support Index". See `https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/index_methodology.md` for documentation.

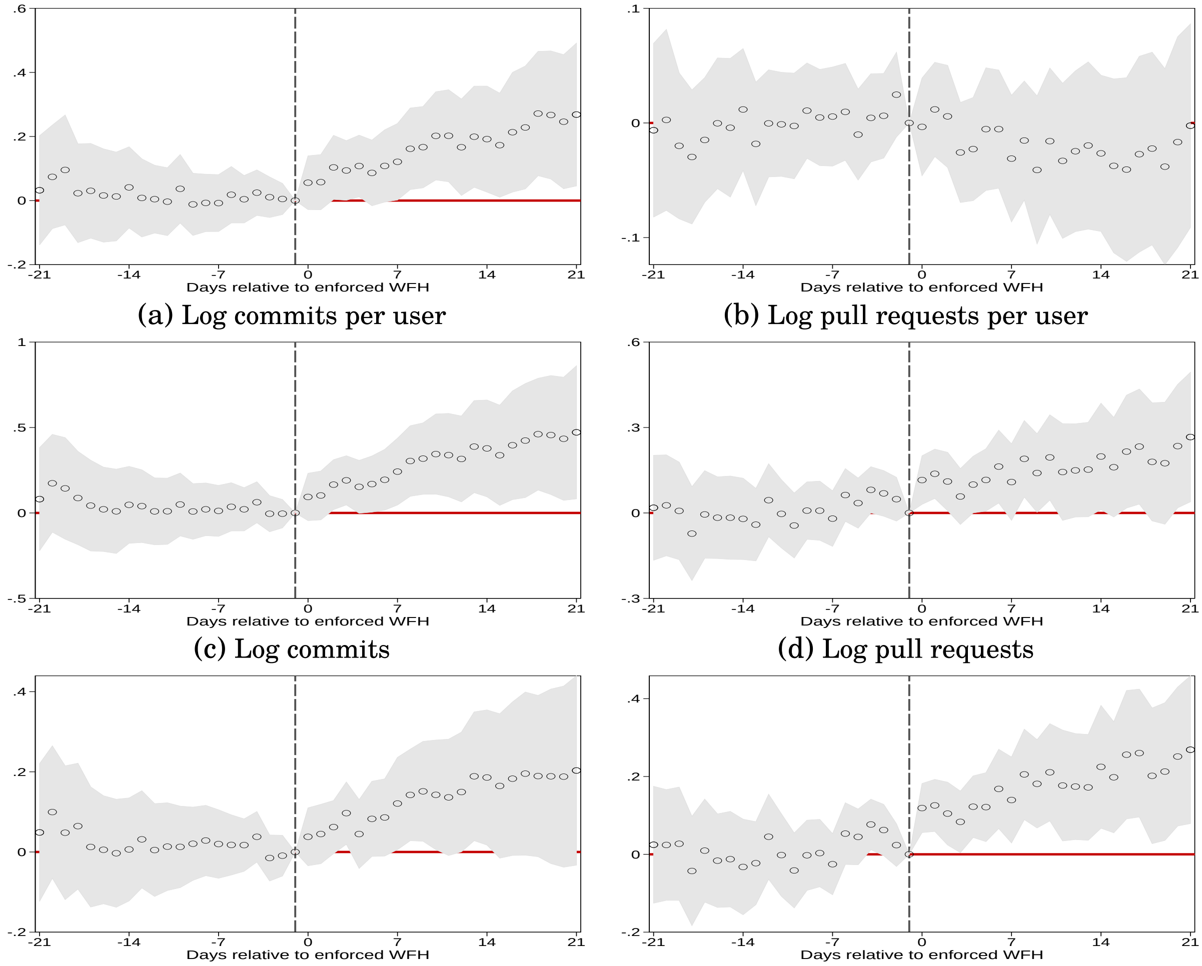
[3] The δ's are intention-to-treat effects. I discuss this in detail in Section V.A.

[4] $60 \approx 100 \times [\exp(.472) - 1]$.

[5] $23 \approx 100 \times [\exp(.203) - 1]$.

[6] $31 \approx 100 \times [\exp(.268) - 1]$.

[7] $31 \approx 100 \times [\exp(.267) - 1]$.



(a) Log commits per user

(b) Log pull requests per user

(c) Log commits

(d) Log pull requests

(e) Log users (commits)

(f) Log users (pull requests)

Figure A22: Event Studies for Productivity

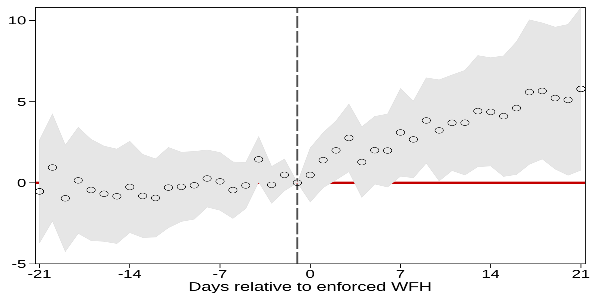
Notes—Event studies documenting changes in productive output, with figures plotting the γ_τ and δ_τ from estimating Equation (1). Day 0 is the date at which the OxCGRT WFH indicator for a country first switches from either a 0 or 1 to a 2 or 3 (Table 1). In the last row, the dependent variable is the log of (1+) the number of recorded users for the respective type of activity (column-wise). All results control for timing group-by-week, date, and country fixed effects, the OxCGRT WFH indicator, two OxCGRT government response indices, and the epidemiology records. Shaded gray areas denote 90% confidence band constructed from standard errors clustered by countries.

$< .02$).[8] Overall, the estimated change in pull requests per user is effectively zero, with an estimated decrease of .2 percent, and is not significant at any conventional level ($p < .978$, see Table A15).[9]

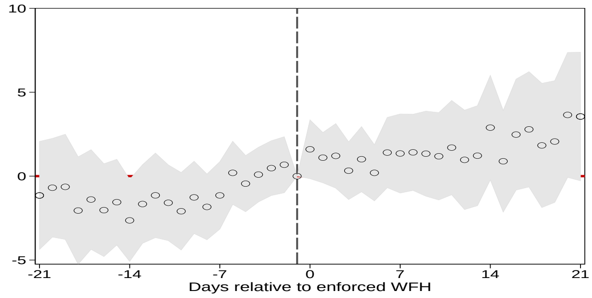
In sum, I take two key insights from the event study results in Figure A27. First is validating state-imposed WFH as an exogenous timing in treatment assignment. The γ_τ estimates, which constitute conditional falsification tests for pretrends, are all virtually zero. This implies minimal anticipatory effect of WFH. I use this finding to motivate the difference-in-differences analyses in Section IV. Second, a substantial portion of the increase in productive output comes from the extensive margin through an increase in active individuals. This implies that for the COVID-19

[8] $31 \approx 100 \times [\exp(.269) - 1]$.

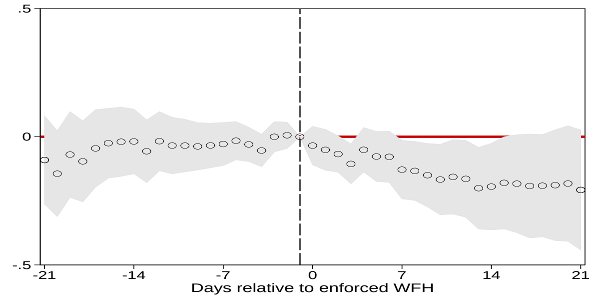
[9] $-.2 \approx 100 \times [\exp(-.002) - 1]$.



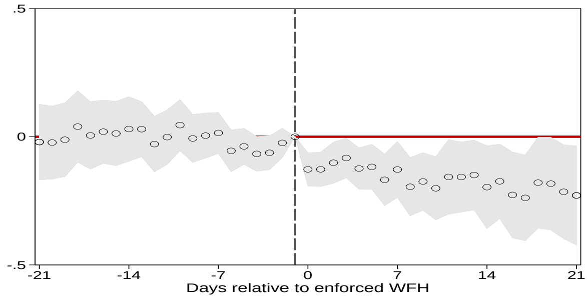
(a) Age of users (commits, ’00 days)



(b) Age of users (pull requests, ’00 days)



(c) New accounts (commits)



(d) New accounts (pull requests)

Figure A23: Event Studies for Age Profile

Notes—Event studies documenting changes in active individual age profile, with figures plotting the γ_τ and δ_τ from estimating Equation (1). Day 0 is the date at which the OxCGRT WFH indicator for a country first switches from either a 0 or 1 to a 2 or 3 (Table 1). In the first row, the dependent variable is the age of individuals, in days, scaled down by 100. In the second row, the dependent variable is share of "new individuals"—ln(1+new individuals) - ln(1+total individuals)—with new individuals defined as accounts created only after the last day of 2019. Shaded gray areas denote 90% confidence band constructed from standard errors clustered by countries.

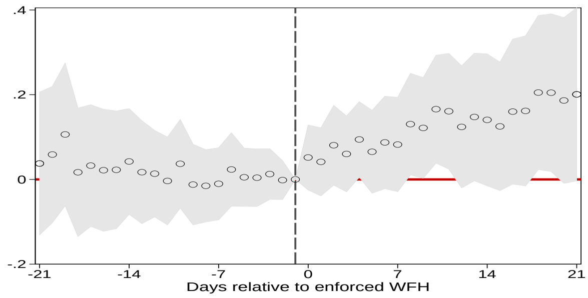
pandemic, disruptions to work and WFH have led to observable structural changes in work patterns on GitHub, where workers are changing what they use at work.

A Changes in Age Profile

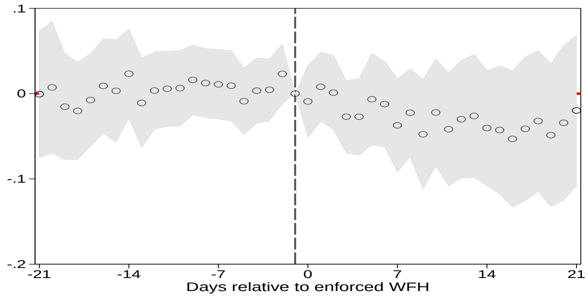
Motivated by the increase in active individuals on the GitHub platform following the closure of workplaces (last row of Figure A27), I repeat the event study analyses with a focus on user composition. I use age profile as the dependent variable and, separately, control for age with productive output as the dependent variables.

Figure A23 plots the estimates from Equation (1), using user account age and share of new accounts as the dependent variables. Overall, the results suggest that the average age of the user accounts is increasing, and there is a decrease in the share of activity from new user accounts. Similar to Figure A27, the results in Figure A23, even with very basic measures, allow us to draw observations of a structural change in work patterns.

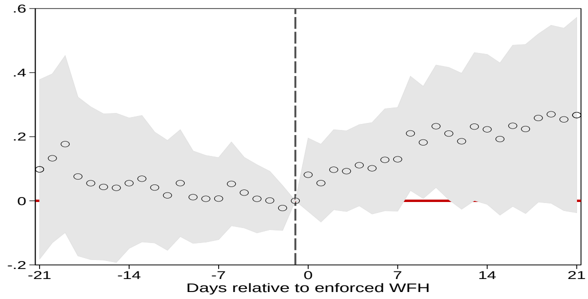
Figure A24 reports the event study results controlling for the age profile of active individuals (user account age). Once I control for the average age of active individuals, the WFH effect is no longer statistically significant (with p-values of



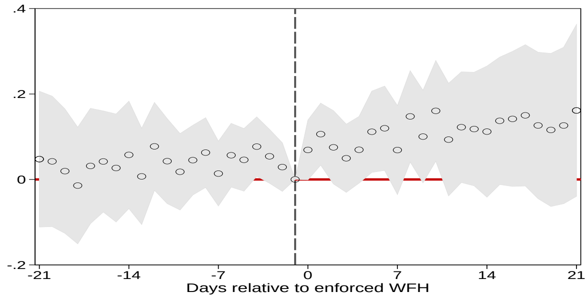
(a) Log commits per user



(b) Log pull requests per user



(c) Log commits



(d) Log pull requests

Figure A24: Event Studies, Controlling for Age Profile

Notes—Event studies documenting changes in productive output, with figures plotting the γ_τ and δ_τ from estimating Equation (1). Day 0 is the date at which the OxCGRT WFH indicator for a country first switches from either a 0 or 1 to a 2 or 3 (Table 1). Identical to first two rows of Figure A27, except with an inclusion of the average age of individuals as a covariate with potentially time-varying effect. Shaded gray areas denote 90% confidence band constructed from standard errors clustered by countries.

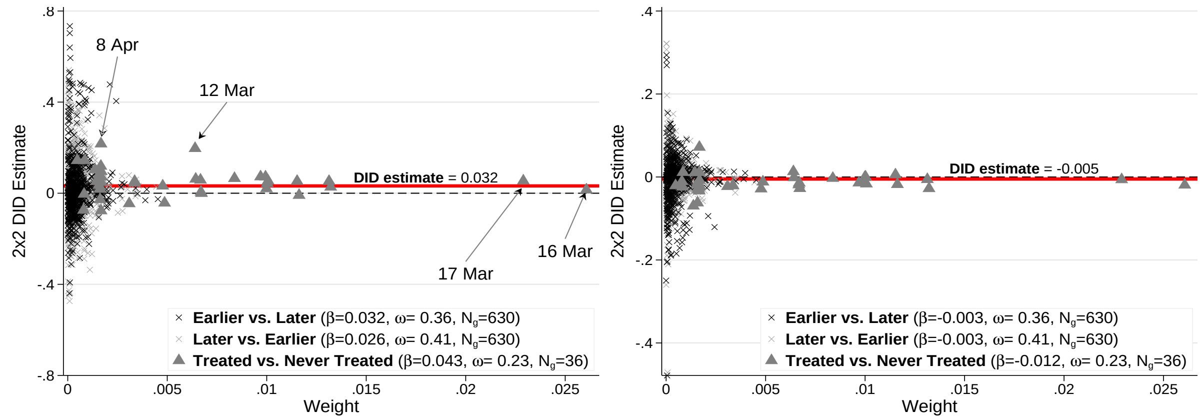
.106 and .149 for commits per user and total commits, respectively, by day 21). For pull requests, what marginally significant result previously found also disappears, with p-values of .712 and .186 for pull requests per user and total pull requests, respectively.[10]

B Decomposition of DID Estimates

One concern with estimating difference-in-differences with variation in treatment timing is that earlier treated cohorts also end up serving as a control to later treated cohorts, and vice versa (Goodman-Bacon 2019). This potentially leads to (predictable) biases when the treatment effect exhibits variation over time (as suggested by Figure A27).

Concretely, suppose that WFH improves productive output but that individuals take up to four weeks to adjust to WFH fully. In this case, when a late treatment cohort has WFH imposed with only two weeks remaining in the sample period and

[10] One might consider adding the lagged value of the dependent variable in the above estimations, but this requires a different (more demanding) set of assumptions for consistency. It can be shown that if the model with a lagged dependent variable is the true model, but one estimates a fixed effects model instead, then the fixed effects estimate constitutes an upper bound of the true effect (**?**).



(a) Commits (b) Pull requests

Figure A25: DECOMPOSITION OF 2×2 DID ESTIMATE

Notes—Plots of the decomposition of the single-coefficient 2x2 difference-in-differences estimate for all possible "2x2" DID estimates, where the dependent variable is log commits/pull requests per user, following Goodman-Bacon (2019). In the context of this study, there are only three groups as indicated in the legend (there is no "Treated vs. Already Treated" group). The red horizontal line indicates the single-coefficient two-way fixed effects difference-in-differences estimate. Also reported are the unconditional DID estimates (β) for the three groups, the weights (ω), and group size (N_g). Dates in the plot indicate Day 0 for the treated group in the (arrowed) comparison groups. Table A2 lists notable countries that fall into the four highlighted groups.

is compared with an early treatment cohort, a difference-in-differences underestimates the WFH effect. This potentially explains the null findings even if WFH indeed improves productive output. To mitigate such concerns, I perform a decomposition of the single difference-in-differences estimate as suggested by Goodman-Bacon (2019).

Figure A25 plots the full set of "2 x 2" DID estimates, where each set corresponds to a combination of groups defined by treatment timing. The red horizontal line indicates the single-coefficient DID estimate, which in the Goodman-Bacon (2019) theorem is the variance-weighted average of the "2 x 2" DID estimates.[11]

I highlight two points here. First, while heterogeneity across comparisons of timing groups is a concern with the staggered rollout of WFH, the three grouped coefficients always have the same sign, with comparable estimated magnitudes. In other words, the concern that the "Later vs. Earlier" timing group comparisons have negative estimates because the evolving trend for the late treated groups has not fully developed, and thus attenuates the overall DID estimate, can be rejected.

Second, and as expected, the "2 x 2" DID estimates with the largest weights come from comparisons to "pure controls" (or the "Never Treated"—countries that never receive statewide imposed WFH in the sample period), and they cluster around zero. Panel (a) of Figure A25 includes annotation for "Day 0" of the treated coun-

[11] So the single-coefficient two-way fixed effects DID estimate would be $\sum_\tau \beta_\tau w_\tau$, where τ indicates one of the three timing groups. In panel (a) of Figure A25 for example, the DID estimate of $0.032 = (0.032 \times 0.36) + (0.026 \times 0.41) + (0.043 \times 0.23)$.

tries for four combinations with the highest weights and estimates.[12]

C Issues as Placebos

In addition to the findings in Section III, I use the opening and closing of issues to show that commits and pull requests are capturing metrics of productive output and not just overall GitHub activity.

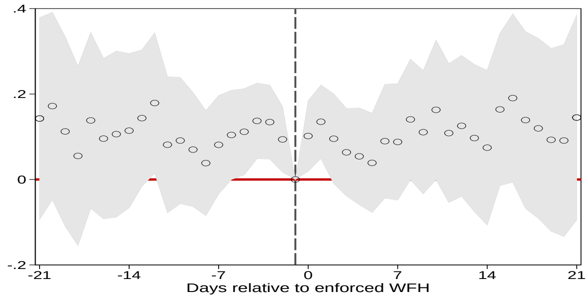
For some context, on top of tracked changes in repositories, GitHub also features an issue-tracking system for repositories. This is where GitHub users can open issues to, among other things, log tasks, report bugs, ask for help, and request features. This is akin to an IT or customer helpdesk issuing tickets to customers and closing the ticket when the issue is resolved, and, to this extent, issues resemble work activity.

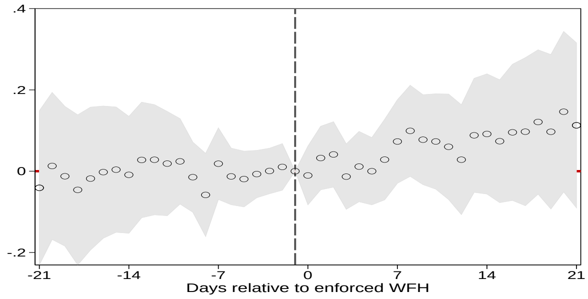
Any user can open issues. Issue openers and repository owners can close issues, and they can close them anytime. However, the opening and closing of issues do not approximate productive output. The opening of issues is usually questions or requests. The closing of issues can be done at the discretion of project contributors. To this extent, issues are useful as a placebo productive metric in that we should not observe substantial changes, even at the extensive margin, arising from the WFH timings.[13]

The event study results in Figure A26 provide evidence that the timing of WFH does not affect the opening and closing of issues, as should be the case if issues are not reliable metrics of productive output.

[12] France, Russia, and Norway are notable countries in this group that disproportionately contribute to the positive DID estimate (Table A2). Notably, the US is not in this group. Figure A3 shows the difference between US observations vs the rest of the world. Individuals in the US microsample tend to be more experienced (older accounts), have more followers, follow fewer people, and are more likely to report their company in their profile.

[13] An issue may be closed without resolution that can be deemed a productive output. Some generic examples of issues closed in ways that do not constitute a productive output: i) issues closed because the issue description is too vague to justify action; ii) inactive issues closed where the discussion thread has been inactive for a long time; iii) issues closed because they are duplicates of existing issues; iv) issues closed because the requested features cannot be implemented in the foreseeable future and are relegated to a “wishlist”; v) issues closed because the requested features have already been considered by the project contributors who have already decided not to follow through; and vi) issues closed with responses that provide workable answers to questions but do not constitute productive output until users raising the questions implement the solutions in their pipeline.



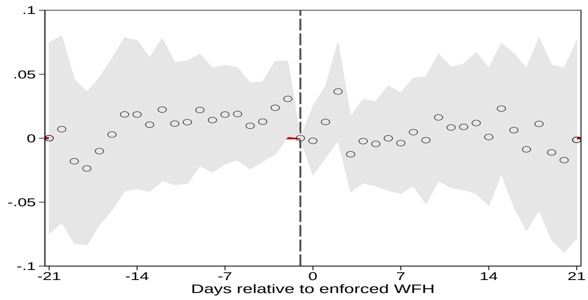


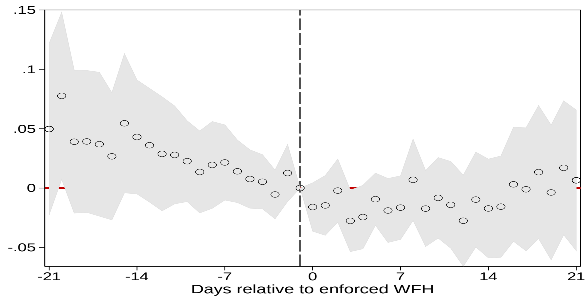
(a) Log opened issues

(b) Log closed issues

Figure A26: Event Studies for Opening and Closing of Issues

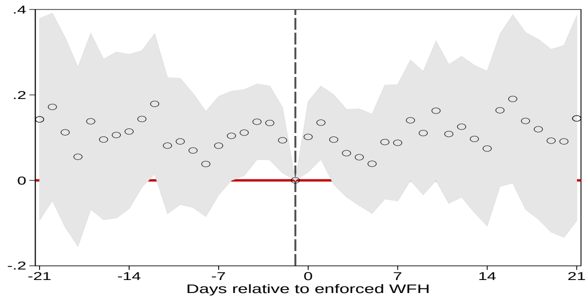
Notes—Event studies documenting changes in opened and closed issues. Day 0 is the date at which the OxCGRT WFH indicator for a country first switches from either a 0 or 1 to a 2 or 3. All results control for timing group-by-week, date, and country fixed effects, the OxCGRT WFH indicator, two OxCGRT government COVID-19 response indices, and the COVID-19 epidemiology records. Results for issues per user and active users are in Appendix D. Shaded gray areas denote 90% confidence band constructed from standard errors clustered by countries.

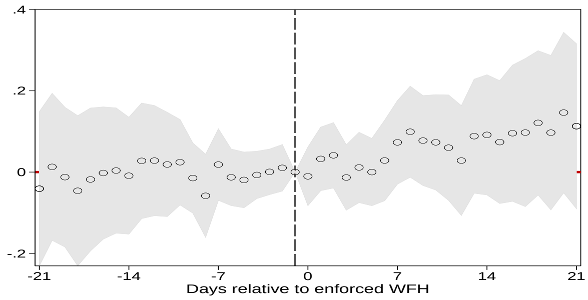




(a) Log opened issues per user

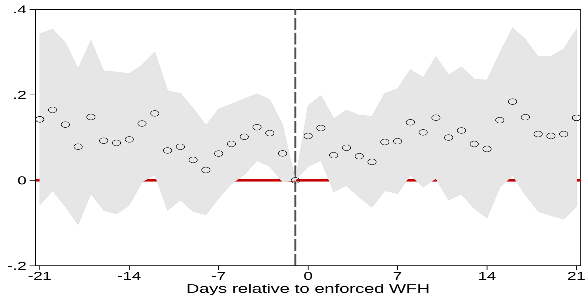
(b) Log closed issues per user

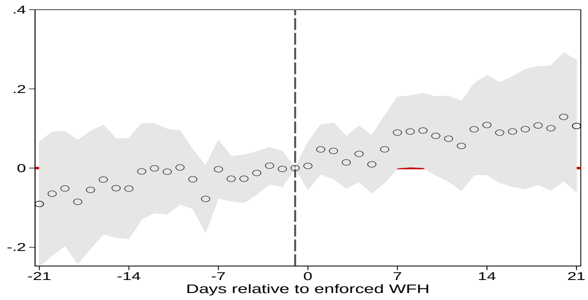




(c) Log opened issues

(d) Log closed issues





(e) Log users (opened issues)

(f) Log users (closed issues)

Figure A27: Event Studies for Opening and Closing of Issues

Notes—Event studies documenting changes in opened and closed issues. Day 0 is the date at which the OxCGRT WFH indicator for a country first switches from either a 0 or 1 to a 2 or 3. In the last row, the dependent variable is the log of (1+) the number of recorded users for the respective type of activity (column-wise). All results control for timing group-by-week, date, and country fixed effects, the OxCGRT WFH indicator, two OxCGRT government COVID-19 response indices, and the COVID-19 epidemiology records. Shaded gray areas denote 90% confidence band constructed from standard errors clustered by countries.

Table A13—*Event Studies Results*

	Commits sample			Pull requests sample		
Dep. var. is:	Log commits per individual (1)	Log commits (2)	Log users (commits) (3)	Log pull requests per individual (4)	Log pull requests (5)	Log users (pull requests) (6)
TimeToTreat = -21	0.032	0.081	0.049	-0.006	0.018	0.025
	(0.103)	(0.182)	(0.104)	(0.046)	(0.111)	(0.091)
TimeToTreat = -20	0.074	0.174	0.100	0.003	0.027	0.024
	(0.098)	(0.173)	(0.100)	(0.048)	(0.107)	(0.086)
TimeToTreat = -19	0.096	0.144	0.048	-0.020	0.007	0.027
	(0.104)	(0.180)	(0.101)	(0.038)	(0.104)	(0.088)
TimeToTreat = -18	0.023	0.087	0.065	-0.030	-0.073	-0.043
	(0.093)	(0.165)	(0.095)	(0.035)	(0.099)	(0.085)
TimeToTreat = -17	0.030	0.043	0.012	-0.015	-0.005	0.010
	(0.089)	(0.161)	(0.091)	(0.033)	(0.093)	(0.080)
TimeToTreat = -16	0.016	0.021	0.006	-0.000	-0.017	-0.016
	(0.088)	(0.149)	(0.081)	(0.034)	(0.087)	(0.073)
TimeToTreat = -15	0.013	0.010	-0.003	-0.004	-0.017	-0.012
	(0.084)	(0.149)	(0.081)	(0.037)	(0.088)	(0.074)
TimeToTreat = -14	0.041	0.048	0.006	0.012	-0.021	-0.032
	(0.077)	(0.136)	(0.078)	(0.032)	(0.086)	(0.074)
TimeToTreat = -13	0.008	0.040	0.032	-0.018	-0.041	-0.023
	(0.074)	(0.129)	(0.073)	(0.033)	(0.077)	(0.065)
TimeToTreat = -12	0.004	0.009	0.005	-0.000	0.045	0.045
	(0.064)	(0.118)	(0.070)	(0.028)	(0.077)	(0.066)
TimeToTreat = -11	-0.003	0.010	0.013	-0.001	-0.003	-0.002
	(0.064)	(0.117)	(0.066)	(0.027)	(0.072)	(0.064)
TimeToTreat = -10	0.037	0.049	0.013	-0.003	-0.044	-0.041
	(0.065)	(0.111)	(0.061)	(0.028)	(0.069)	(0.058)
TimeToTreat = -9	-0.012	0.009	0.021	0.011	0.008	-0.002
	(0.059)	(0.098)	(0.055)	(0.025)	(0.061)	(0.055)
TimeToTreat = -8	-0.007	0.021	0.029	0.005	0.008	0.003
	(0.054)	(0.093)	(0.053)	(0.025)	(0.063)	(0.052)
TimeToTreat = -7	-0.008	0.012	0.020	0.006	-0.020	-0.025
	(0.054)	(0.090)	(0.052)	(0.026)	(0.059)	(0.047)
TimeToTreat = -6	0.018	0.036	0.018	0.010	0.063	0.053
	(0.053)	(0.085)	(0.045)	(0.026)	(0.056)	(0.048)
TimeToTreat = -5	0.004	0.021	0.017	-0.010	0.035	0.045
	(0.045)	(0.077)	(0.040)	(0.024)	(0.053)	(0.043)
TimeToTreat = -4	0.025	0.063	0.038	0.004	0.081	0.077^{*}
	(0.043)	(0.073)	(0.038)	(0.023)	(0.049)	(0.039)
TimeToTreat = -3	0.010	-0.005	-0.015	0.006	0.069	0.062
	(0.038)	(0.064)	(0.035)	(0.022)	(0.048)	(0.040)
TimeToTreat = -2	0.005	-0.004	-0.009	0.025	0.048	0.024
	(0.029)	(0.050)	(0.031)	(0.022)	(0.047)	(0.033)
TimeToTreat = 0	0.056	0.094	0.038	-0.003	0.116^{**}	0.119^{***}
	(0.051)	(0.084)	(0.044)	(0.026)	(0.052)	(0.038)
TimeToTreat = 1	0.058	0.102	0.045	0.012	0.138^{***}	0.126^{***}
	(0.052)	(0.086)	(0.045)	(0.025)	(0.052)	(0.040)
TimeToTreat = 2	0.103^{*}	0.166^{*}	0.062	0.006	0.110^{*}	0.105^{**}
	(0.061)	(0.088)	(0.040)	(0.027)	(0.062)	(0.049)
TimeToTreat = 3	0.094^{*}	0.191^{**}	0.097^{**}	-0.026	0.058	0.083^{*}
	(0.056)	(0.087)	(0.047)	(0.026)	(0.059)	(0.048)
TimeToTreat = 4	0.108^{*}	0.153	0.045	-0.023	0.100	0.122^{**}
	(0.058)	(0.094)	(0.052)	(0.027)	(0.060)	(0.048)
TimeToTreat = 5	0.086	0.169^{*}	0.083	-0.005	0.116^{*}	0.121^{**}
	(0.062)	(0.099)	(0.057)	(0.032)	(0.066)	(0.054)
TimeToTreat = 6	0.108	0.194^{*}	0.086	-0.005	0.163^{**}	0.168^{***}
	(0.068)	(0.108)	(0.058)	(0.031)	(0.077)	(0.062)
TimeToTreat = 7	0.121^{*}	0.242^{**}	0.121^{*}	-0.031	0.109	0.140^{**}
	(0.072)	(0.118)	(0.070)	(0.033)	(0.081)	(0.067)
TimeToTreat = 8	0.162^{**}	0.304^{**}	0.142^{**}	-0.015	0.190^{**}	0.205^{***}
	(0.077)	(0.125)	(0.069)	(0.031)	(0.081)	(0.070)
TimeToTreat = 9	0.167^{**}	0.318^{**}	0.151^{**}	-0.041	0.140^{*}	0.181^{***}
	(0.077)	(0.126)	(0.075)	(0.039)	(0.083)	(0.069)
TimeToTreat = 10	0.202^{**}	0.345^{**}	0.143^{*}	-0.016	0.195^{**}	0.211^{***}
	(0.083)	(0.142)	(0.083)	(0.039)	(0.090)	(0.076)
TimeToTreat = 11	0.202^{**}	0.339^{**}	0.136	-0.033	0.144	0.177^{**}
	(0.087)	(0.147)	(0.088)	(0.041)	(0.103)	(0.086)
TimeToTreat = 12	0.166^{*}	0.316^{**}	0.150^{*}	-0.025	0.149	0.174^{**}
	(0.091)	(0.152)	(0.090)	(0.042)	(0.099)	(0.082)
TimeToTreat = 13	0.199^{**}	0.388^{**}	0.189^{*}	-0.020	0.152	0.172^{**}
	(0.095)	(0.163)	(0.097)	(0.044)	(0.100)	(0.082)
TimeToTreat = 14	0.192^{*}	0.378^{**}	0.186^{*}	-0.027	0.198^{*}	0.225^{**}
	(0.100)	(0.171)	(0.102)	(0.041)	(0.113)	(0.095)
TimeToTreat = 15	0.173^{*}	0.338^{*}	0.165	-0.037	0.161	0.198^{**}
	(0.098)	(0.177)	(0.109)	(0.046)	(0.106)	(0.086)
TimeToTreat = 16	0.213^{*}	0.396^{**}	0.183	-0.041	0.215^{*}	0.256^{**}
	(0.113)	(0.192)	(0.116)	(0.048)	(0.120)	(0.100)
TimeToTreat = 17	0.228^{*}	0.424^{**}	0.196	-0.027	0.233^{*}	0.260^{***}
	(0.116)	(0.202)	(0.123)	(0.052)	(0.122)	(0.099)
TimeToTreat = 18	0.272^{**}	0.461^{**}	0.189	-0.022	0.179	0.202^{*}
	(0.117)	(0.198)	(0.122)	(0.051)	(0.125)	(0.105)
TimeToTreat = 19	0.267^{**}	0.456^{**}	0.189	-0.038	0.175	0.213^{**}
	(0.121)	(0.210)	(0.132)	(0.052)	(0.129)	(0.107)
TimeToTreat = 20	0.246^{*}	0.434^{**}	0.188	-0.017	0.235^{*}	0.251^{**}
	(0.126)	(0.218)	(0.137)	(0.056)	(0.131)	(0.108)
TimeToTreat = 21	0.268^{**}	0.472^{**}	0.203	-0.002	0.267^{*}	0.269^{**}
	(0.135)	(0.235)	(0.143)	(0.054)	(0.137)	(0.115)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Timing group-by-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.627	0.893	0.931	0.379	0.899	0.913
Country Observations	153	153	153	153	153	153
Country-day Observations	27,844	27,844	27,844	27,844	27,844	27,844

Notes—Table reports regression coefficients from estimating the event-study specification in Equation (1), and corresponds to Figure A27. *lag*τ coefficients refer to the $T_c - \tau$ coefficients while *lead*τ coefficients refer to the $T_c + \tau$ coefficients, where T_c is day 0 of the state-imposed WFH. *lag1* ($T_c - 1$) is the omitted period. Timing group-by-week fixed effects is the interaction of the timing groups of the state-imposed WFH, defined by day 0, and the week-of-year dummies. Standard errors are clustered at countries.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

Table A14—*Event Studies Results with Age Profile*

	Commits sample				Pull requests sample			
Dep. var. is:	Individual age (1)	New users (2)	Log commits per individual (3)	Log commits (4)	Individual age (5)	New users (6)	Log pull requests per individual (7)	Log pull requests (8)
TimeToTreat = -21	−0.530	−0.091	0.038	0.098	−1.151	−0.021	−0.001	0.048
	(1.915)	(0.104)	(0.102)	(0.169)	(1.946)	(0.089)	(0.045)	(0.096)
TimeToTreat = -20	0.942	−0.144	0.059	0.133	−0.690	−0.023	0.007	0.042
	(1.989)	(0.101)	(0.097)	(0.159)	(1.776)	(0.086)	(0.047)	(0.092)
TimeToTreat = -19	−0.957	−0.069	0.106	0.177	−0.638	−0.012	−0.015	0.019
	(1.980)	(0.101)	(0.102)	(0.167)	(1.894)	(0.087)	(0.038)	(0.088)
TimeToTreat = -18	0.147	−0.096	0.017	0.076	−2.051	0.040	−0.020	−0.014
	(1.975)	(0.096)	(0.092)	(0.150)	(1.932)	(0.084)	(0.034)	(0.082)
TimeToTreat = -17	−0.445	−0.045	0.033	0.055	−1.393	0.005	−0.008	0.032
	(1.887)	(0.091)	(0.087)	(0.144)	(1.795)	(0.080)	(0.033)	(0.082)
TimeToTreat = -16	−0.675	−0.025	0.022	0.043	−2.026	0.020	0.009	0.042
	(1.776)	(0.082)	(0.087)	(0.138)	(1.670)	(0.075)	(0.033)	(0.072)
TimeToTreat = -15	−0.834	−0.019	0.023	0.040	−1.550	0.013	0.003	0.027
	(1.761)	(0.082)	(0.084)	(0.141)	(1.544)	(0.076)	(0.036)	(0.076)
TimeToTreat = -14	−0.257	−0.018	0.042	0.055	−2.638*	0.030	0.023	0.058
	(1.702)	(0.076)	(0.075)	(0.123)	(1.477)	(0.076)	(0.032)	(0.076)
TimeToTreat = -13	−0.812	−0.057	0.017	0.069	−1.661	0.029	−0.011	0.007
	(1.550)	(0.074)	(0.073)	(0.119)	(1.415)	(0.065)	(0.032)	(0.068)
TimeToTreat = -12	−0.936	−0.017	0.014	0.041	−1.144	−0.029	0.004	0.077
	(1.458)	(0.070)	(0.062)	(0.105)	(1.523)	(0.065)	(0.027)	(0.062)
TimeToTreat = -11	−0.296	−0.034	−0.004	0.017	−1.587	−0.002	0.006	0.043
	(1.496)	(0.067)	(0.063)	(0.104)	(1.363)	(0.064)	(0.027)	(0.060)
TimeToTreat = -10	−0.250	−0.034	0.037	0.055	−2.092	0.045	0.006	0.018
	(1.292)	(0.062)	(0.063)	(0.101)	(1.395)	(0.060)	(0.027)	(0.054)
TimeToTreat = -9	−0.156	−0.038	−0.012	0.011	−1.267	−0.007	0.016	0.045
	(1.263)	(0.056)	(0.058)	(0.087)	(1.301)	(0.057)	(0.025)	(0.049)
TimeToTreat = -8	0.264	−0.034	−0.015	0.006	−1.834	0.004	0.012	0.063
	(1.065)	(0.053)	(0.052)	(0.082)	(1.184)	(0.053)	(0.024)	(0.049)
TimeToTreat = -7	0.087	−0.028	−0.010	0.007	−1.148	0.015	0.011	0.014
	(1.078)	(0.051)	(0.051)	(0.077)	(1.214)	(0.048)	(0.025)	(0.046)
TimeToTreat = -6	−0.454	−0.015	0.023	0.053	0.196	−0.055	0.009	0.057
	(1.054)	(0.045)	(0.052)	(0.079)	(1.136)	(0.049)	(0.025)	(0.045)
TimeToTreat = -5	−0.166	−0.030	0.005	0.025	−0.447	−0.038	−0.009	0.046
	(0.858)	(0.040)	(0.042)	(0.067)	(1.012)	(0.043)	(0.024)	(0.044)
TimeToTreat = -4	1.444*	−0.054	0.004	0.006	0.093	−0.067	0.003	0.077*
	(0.844)	(0.038)	(0.041)	(0.064)	(0.984)	(0.041)	(0.023)	(0.042)
TimeToTreat = -3	−0.127	−0.000	0.013	0.001	0.478	−0.063	0.004	0.054
	(0.684)	(0.036)	(0.036)	(0.055)	(0.987)	(0.040)	(0.022)	(0.038)
TimeToTreat = -2	0.486	0.006	−0.002	−0.022	0.679	−0.024	0.023	0.029
	(0.591)	(0.031)	(0.028)	(0.042)	(1.009)	(0.035)	(0.021)	(0.034)
TimeToTreat = 0	0.481	−0.035	0.052	0.081	1.600	−0.127***	−0.009	0.069
	(1.007)	(0.045)	(0.046)	(0.069)	(1.059)	(0.039)	(0.025)	(0.042)
TimeToTreat = 1	1.390	−0.051	0.042	0.055	1.101	−0.127***	0.008	0.106**
	(1.023)	(0.048)	(0.049)	(0.073)	(0.906)	(0.041)	(0.025)	(0.044)
TimeToTreat = 2	1.996*	−0.068	0.081	0.097	1.207	−0.101**	0.001	0.075
	(1.100)	(0.043)	(0.057)	(0.076)	(1.162)	(0.049)	(0.026)	(0.052)
TimeToTreat = 3	2.766**	−0.106**	0.060	0.093	0.324	−0.083*	−0.027	0.050
	(1.260)	(0.047)	(0.054)	(0.076)	(1.038)	(0.047)	(0.026)	(0.048)
TimeToTreat = 4	1.275	−0.051	0.094*	0.111	1.008	−0.124**	−0.027	0.069
	(1.314)	(0.052)	(0.054)	(0.077)	(1.173)	(0.049)	(0.027)	(0.047)
TimeToTreat = 5	2.004	−0.077	0.065	0.101	0.197	−0.118**	−0.007	0.112*
	(1.260)	(0.059)	(0.059)	(0.086)	(1.010)	(0.053)	(0.032)	(0.058)
TimeToTreat = 6	1.987	−0.078	0.087	0.128	1.404	−0.168***	−0.012	0.120**
	(1.361)	(0.060)	(0.066)	(0.096)	(1.266)	(0.061)	(0.030)	(0.060)
TimeToTreat = 7	3.101*	−0.128*	0.082	0.130	1.350	−0.128*	−0.037	0.069
	(1.632)	(0.069)	(0.067)	(0.098)	(1.424)	(0.066)	(0.033)	(0.063)
TimeToTreat = 8	2.671*	−0.133*	0.131*	0.210*	1.417	−0.195***	−0.022	0.148**
	(1.430)	(0.070)	(0.072)	(0.108)	(1.373)	(0.069)	(0.031)	(0.065)
TimeToTreat = 9	3.840**	−0.150**	0.122*	0.182*	1.339	−0.175**	−0.048	0.100
	(1.590)	(0.075)	(0.072)	(0.106)	(1.532)	(0.068)	(0.039)	(0.065)
TimeToTreat = 10	3.228*	−0.167**	0.166**	0.233**	1.184	−0.201***	−0.022	0.161**
	(1.884)	(0.083)	(0.077)	(0.116)	(1.574)	(0.074)	(0.038)	(0.071)
TimeToTreat = 11	3.698**	−0.157*	0.161*	0.210*	1.699	−0.157*	−0.042	0.093
	(1.782)	(0.088)	(0.083)	(0.125)	(1.698)	(0.088)	(0.040)	(0.080)
TimeToTreat = 12	3.703*	−0.164*	0.124	0.186	0.971	−0.157*	−0.030	0.122
	(1.950)	(0.091)	(0.087)	(0.128)	(1.790)	(0.083)	(0.042)	(0.078)
TimeToTreat = 13	4.416**	−0.201**	0.147	0.232*	1.218	−0.149*	−0.026	0.118
	(2.070)	(0.096)	(0.091)	(0.140)	(1.801)	(0.082)	(0.044)	(0.080)
TimeToTreat = 14	4.369**	−0.195*	0.141	0.223	2.890	−0.197**	−0.040	0.112
	(2.017)	(0.102)	(0.094)	(0.141)	(1.881)	(0.098)	(0.041)	(0.093)
TimeToTreat = 15	4.106*	−0.180*	0.125	0.193	0.886	−0.174**	−0.043	0.137
	(2.248)	(0.109)	(0.092)	(0.144)	(1.828)	(0.088)	(0.045)	(0.090)
TimeToTreat = 16	4.603*	−0.183	0.160	0.234	2.476	−0.227**	−0.053	0.142
	(2.474)	(0.115)	(0.103)	(0.152)	(1.997)	(0.101)	(0.048)	(0.096)
TimeToTreat = 17	5.590**	−0.192	0.162	0.224	2.788	−0.239**	−0.041	0.150
	(2.691)	(0.123)	(0.107)	(0.160)	(2.075)	(0.101)	(0.051)	(0.100)
TimeToTreat = 18	5.659**	−0.191	0.205*	0.258	1.831	−0.179*	−0.032	0.126
	(2.536)	(0.120)	(0.110)	(0.159)	(2.237)	(0.107)	(0.050)	(0.104)
TimeToTreat = 19	5.218*	−0.189	0.205*	0.270	2.063	−0.183*	−0.049	0.116
	(2.645)	(0.131)	(0.112)	(0.168)	(2.191)	(0.109)	(0.051)	(0.108)
TimeToTreat = 20	5.111*	−0.183	0.186	0.254	3.648	−0.215*	−0.034	0.126
	(2.810)	(0.136)	(0.118)	(0.172)	(2.250)	(0.111)	(0.055)	(0.111)
TimeToTreat = 21	5.786*	−0.208	0.201	0.267	3.553	−0.229*	−0.020	0.161
	(3.028)	(0.141)	(0.123)	(0.184)	(2.315)	(0.117)	(0.053)	(0.121)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Timing group-by-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.673	0.924	0.663	0.927	0.664	0.903	0.412	0.937
Country Observations	153	153	153	153	153	153	153	153
Country-day Observations	27,844	27,844	27,844	27,844	27,844	27,844	27,844	27,844

Notes—Table reports regression coefficients from estimating the event-study specification in Equation (1), corresponding to Figure A23 and Figure A24. In columns (1) and (5), the dependent variable is the average age (in days) of active individuals by day. In columns (2) and (6), the dependent variable is log of the share of active users who are new to the GitHub platform—[log(1 + new users) - log(1 + total users)]—where new users are those whose accounts are created after the last day of 2019. *lag*τ coefficients refer to the $T_c - \tau$ coefficients while *lead*τ coefficients refer to the $T_c + \tau$ coefficients, where T_c is day 0 of the state-imposed WFH. *lag1* ($T_c - 1$) is the omitted period. Timing group-by-week fixed effects is the interaction of the timing groups of the state-imposed WFH, defined by day 0, and the week-of-year dummies. Standard errors are clustered at countries.

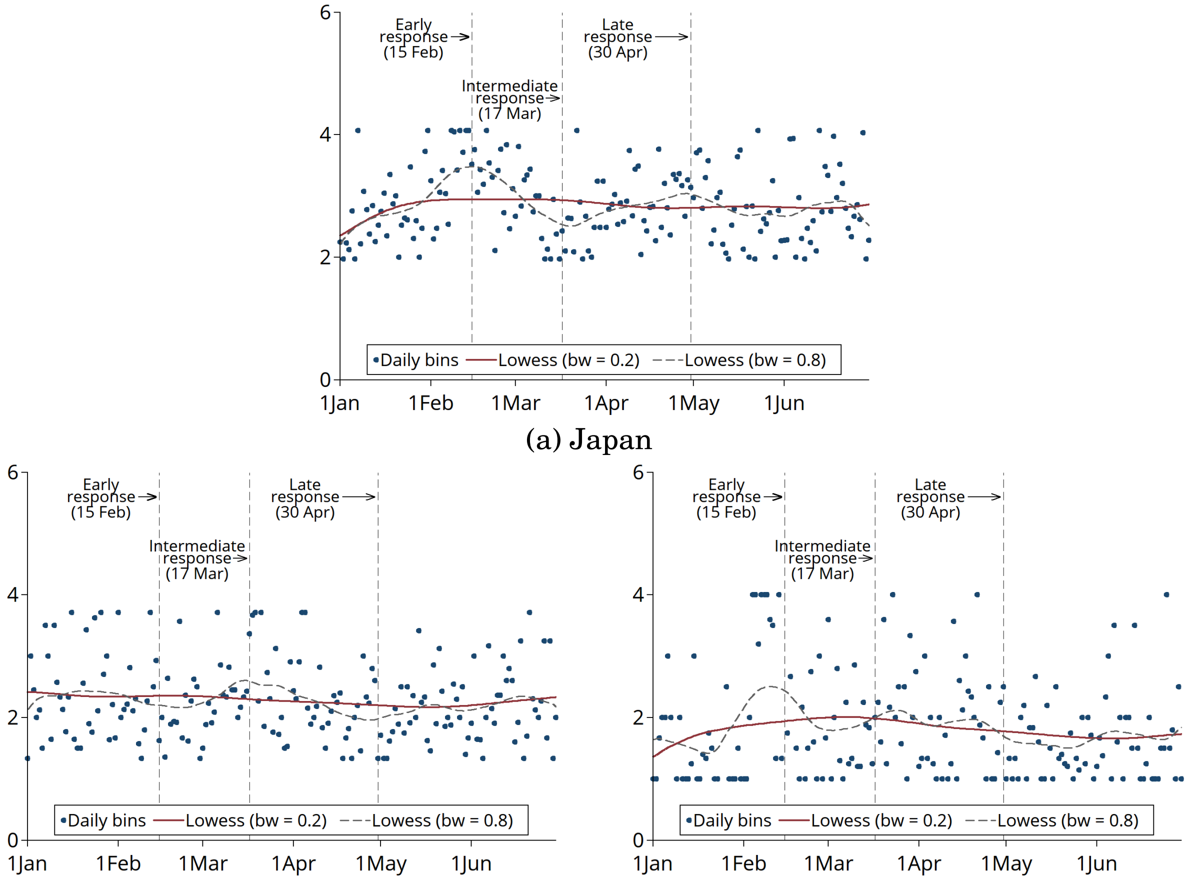
*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.

Table A15—Event Studies Results

Dep. var. is:	Opened issues sample: Log opened issues per individual (1)	Opened issues sample: Log opened issues (2)	Opened issues sample: Log users (opened issues) (3)	Closed issues sample: Log closed issues per individual (4)	Closed issues sample: Log closed issues (5)	Closed issues sample: Log users (closed issues) (6)
TimeToTreat = -21	0.032	0.081	0.049	−0.006	0.018	0.025
	(0.103)	(0.182)	(0.104)	(0.046)	(0.111)	(0.091)
TimeToTreat = -20	0.074	0.174	0.100	0.003	0.027	0.024
	(0.098)	(0.173)	(0.100)	(0.048)	(0.107)	(0.086)
TimeToTreat = -19	0.096	0.144	0.048	−0.020	0.007	0.027
	(0.104)	(0.180)	(0.101)	(0.038)	(0.104)	(0.088)
TimeToTreat = -18	0.023	0.087	0.065	−0.030	−0.073	−0.043
	(0.093)	(0.165)	(0.095)	(0.035)	(0.099)	(0.085)
TimeToTreat = -17	0.030	0.043	0.012	−0.015	−0.005	0.010
	(0.089)	(0.161)	(0.091)	(0.033)	(0.093)	(0.080)
TimeToTreat = -16	0.016	0.021	0.006	−0.000	−0.017	−0.016
	(0.088)	(0.149)	(0.081)	(0.034)	(0.087)	(0.073)
TimeToTreat = -15	0.013	0.010	−0.003	−0.004	−0.017	−0.012
	(0.084)	(0.149)	(0.081)	(0.037)	(0.088)	(0.074)
TimeToTreat = -14	0.041	0.048	0.006	0.012	−0.021	−0.032
	(0.077)	(0.136)	(0.078)	(0.032)	(0.086)	(0.074)
TimeToTreat = -13	0.008	0.040	0.032	−0.018	−0.041	−0.023
	(0.074)	(0.129)	(0.073)	(0.033)	(0.077)	(0.065)
TimeToTreat = -12	0.004	0.009	0.005	−0.000	0.045	0.045
	(0.064)	(0.118)	(0.070)	(0.028)	(0.077)	(0.066)
TimeToTreat = -11	−0.003	0.010	0.013	−0.001	−0.003	−0.002
	(0.064)	(0.117)	(0.066)	(0.027)	(0.072)	(0.064)
TimeToTreat = -10	0.037	0.049	0.013	−0.003	−0.044	−0.041
	(0.065)	(0.111)	(0.061)	(0.028)	(0.069)	(0.058)
TimeToTreat = -9	−0.012	0.009	0.021	0.011	0.008	−0.002
	(0.059)	(0.098)	(0.055)	(0.025)	(0.061)	(0.055)
TimeToTreat = -8	−0.007	0.021	0.029	0.005	0.008	0.003
	(0.054)	(0.093)	(0.053)	(0.025)	(0.063)	(0.052)
TimeToTreat = -7	−0.008	0.012	0.020	0.006	−0.020	−0.025
	(0.054)	(0.090)	(0.052)	(0.026)	(0.059)	(0.047)
TimeToTreat = -6	0.018	0.036	0.018	0.010	0.063	0.053
	(0.053)	(0.085)	(0.045)	(0.026)	(0.056)	(0.048)
TimeToTreat = -5	0.004	0.021	0.017	−0.010	0.035	0.045
	(0.045)	(0.077)	(0.040)	(0.024)	(0.053)	(0.043)
TimeToTreat = -4	0.025	0.063	0.038	0.004	0.081	0.077*
	(0.043)	(0.073)	(0.038)	(0.023)	(0.049)	(0.039)
TimeToTreat = -3	0.010	−0.005	−0.015	0.006	0.069	0.062
	(0.038)	(0.064)	(0.035)	(0.022)	(0.048)	(0.040)
TimeToTreat = -2	0.005	−0.004	−0.009	0.025	0.048	0.024
	(0.029)	(0.050)	(0.031)	(0.022)	(0.047)	(0.033)
TimeToTreat = 0	0.056	0.094	0.038	−0.003	0.116**	0.119***
	(0.051)	(0.084)	(0.044)	(0.026)	(0.052)	(0.038)
TimeToTreat = 1	0.058	0.102	0.045	0.012	0.138***	0.126***
	(0.052)	(0.086)	(0.045)	(0.025)	(0.052)	(0.040)
TimeToTreat = 2	0.103*	0.166*	0.062	0.006	0.110*	0.105**
	(0.061)	(0.088)	(0.040)	(0.027)	(0.062)	(0.049)
TimeToTreat = 3	0.094*	0.191**	0.097**	−0.026	0.058	0.083*
	(0.056)	(0.087)	(0.047)	(0.026)	(0.059)	(0.048)
TimeToTreat = 4	0.108*	0.153	0.045	−0.023	0.100	0.122**
	(0.058)	(0.094)	(0.052)	(0.027)	(0.060)	(0.048)
TimeToTreat = 5	0.086	0.169*	0.083	−0.005	0.116*	0.121**
	(0.062)	(0.099)	(0.057)	(0.032)	(0.066)	(0.054)
TimeToTreat = 6	0.108	0.194*	0.086	−0.005	0.163**	0.168***
	(0.068)	(0.108)	(0.058)	(0.031)	(0.077)	(0.062)
TimeToTreat = 7	0.121*	0.242**	0.121*	−0.031	0.109	0.140**
	(0.072)	(0.118)	(0.070)	(0.033)	(0.081)	(0.067)
TimeToTreat = 8	0.162**	0.304**	0.142**	−0.015	0.190**	0.205***
	(0.077)	(0.125)	(0.069)	(0.031)	(0.081)	(0.070)
TimeToTreat = 9	0.167**	0.318**	0.151**	−0.041	0.140*	0.181***
	(0.077)	(0.126)	(0.075)	(0.039)	(0.083)	(0.069)
TimeToTreat = 10	0.202**	0.345**	0.143*	−0.016	0.195**	0.211***
	(0.083)	(0.142)	(0.083)	(0.039)	(0.090)	(0.076)
TimeToTreat = 11	0.202**	0.339**	0.136	−0.033	0.144	0.177**
	(0.087)	(0.147)	(0.088)	(0.041)	(0.103)	(0.086)
TimeToTreat = 12	0.166*	0.316**	0.150*	−0.025	0.149	0.174**
	(0.091)	(0.152)	(0.090)	(0.042)	(0.099)	(0.082)
TimeToTreat = 13	0.199**	0.388**	0.189*	−0.020	0.152	0.172**
	(0.095)	(0.163)	(0.097)	(0.044)	(0.100)	(0.082)
TimeToTreat = 14	0.192*	0.378**	0.186*	−0.027	0.198*	0.225**
	(0.100)	(0.171)	(0.102)	(0.041)	(0.113)	(0.095)
TimeToTreat = 15	0.173*	0.338*	0.165	−0.037	0.161	0.198**
	(0.098)	(0.177)	(0.109)	(0.046)	(0.106)	(0.086)
TimeToTreat = 16	0.213*	0.396**	0.183	−0.041	0.215*	0.256**
	(0.113)	(0.192)	(0.116)	(0.048)	(0.120)	(0.100)
TimeToTreat = 17	0.228*	0.424**	0.196	−0.027	0.233*	0.260***
	(0.116)	(0.202)	(0.123)	(0.052)	(0.122)	(0.099)
TimeToTreat = 18	0.272**	0.461**	0.189	−0.022	0.179	0.202*
	(0.117)	(0.198)	(0.122)	(0.051)	(0.125)	(0.105)
TimeToTreat = 19	0.267**	0.456**	0.189	−0.038	0.175	0.213**
	(0.121)	(0.210)	(0.132)	(0.052)	(0.129)	(0.107)
TimeToTreat = 20	0.246*	0.434**	0.188	−0.017	0.235*	0.251**
	(0.126)	(0.218)	(0.137)	(0.056)	(0.131)	(0.108)
TimeToTreat = 21	0.268**	0.472**	0.203	−0.002	0.267*	0.269**
	(0.135)	(0.235)	(0.143)	(0.054)	(0.137)	(0.115)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Timing group-by-week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.627	0.893	0.931	0.379	0.899	0.913
Country Observations	153	153	153	153	153	153
Country-day Observations	27,844	27,844	27,844	27,844	27,844	27,844

Notes—Table reports regression coefficients from estimating the event-study specification in Equation (1), and corresponds to Figure A27. *lag*τ coefficients refer to the $T_c - \tau$ coefficients while *lead*τ coefficients refer to the $T_c + \tau$ coefficients, where T_c is day 0 of the state-imposed WFH. *lag1* ($T_c - 1$) is the omitted period. Timing group-by-week fixed effects is the interaction of the timing groups of the state-imposed WFH, defined by day 0, and the week-of-year dummies. Standard errors are clustered at countries.

*** Significant at the 1 per cent level.
** Significant at the 5 per cent level.
* Significant at the 10 per cent level.



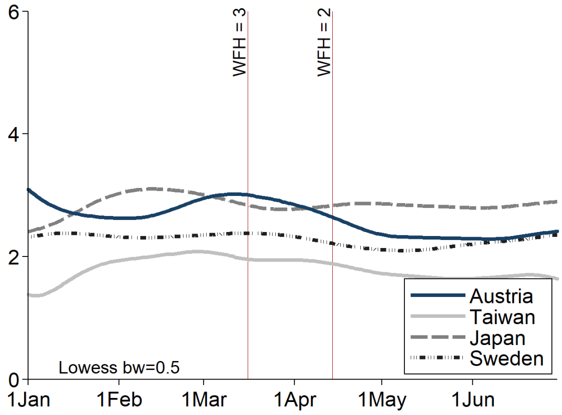
(a) Japan

(b) Sweden

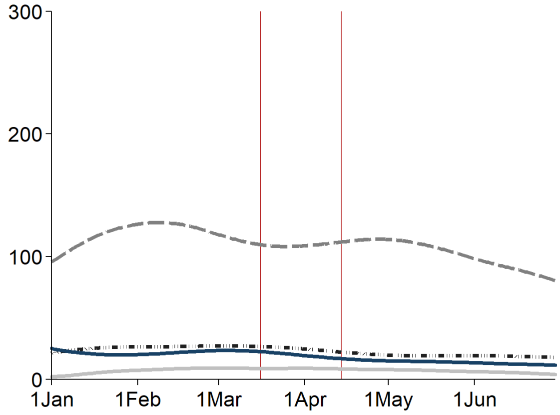
(c) Taiwan

Figure A28: Base countries' path plot

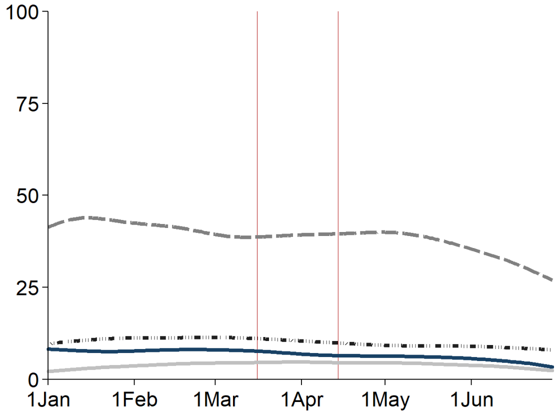
Notes. Path of user activity for those located in Japan, Sweden, and Taiwan—three notable countries that never imposed lockdown/closure of workplaces in the sample period. The vertical lines indicate general periods of global lockdown (see Figures A5 and A6). Variables winsorized at 5% and 95%. Line plots are from locally weighted scatterplot smoothing with the stated bandwidths.



(a) Commits per user-repo



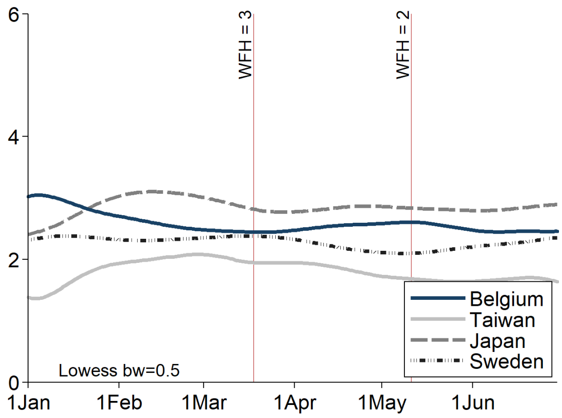
(b) Commits



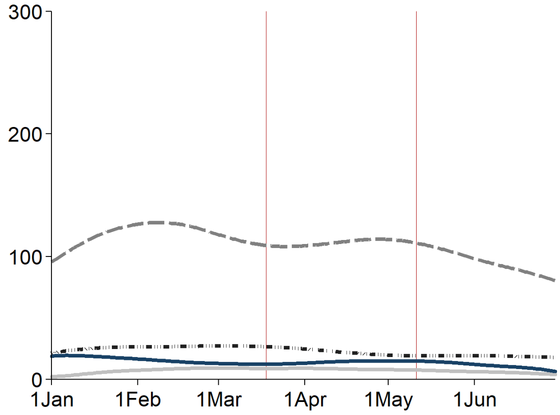
(c) Active user-repos

Figure A29: Austria's path plot

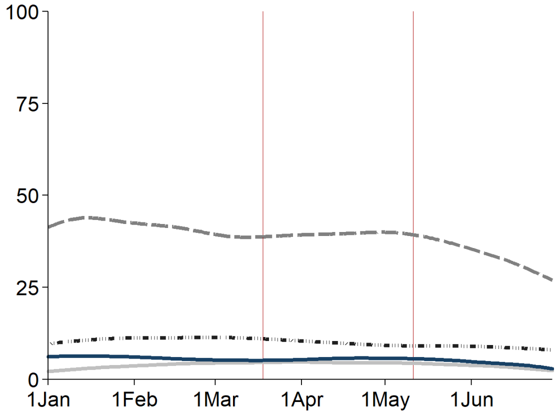
Notes. Path of user activity for those located in Austria (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). Austria imposed mandatory WFH for all-but-essential workplaces (WFH = 3) on March 16; and then relaxed this to mandatory WFH for some sectors (WFH = 2) starting April 14. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



(a) Commits per user-repo



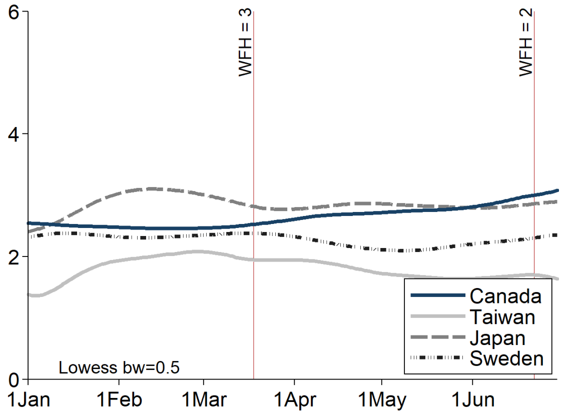
(b) Commits



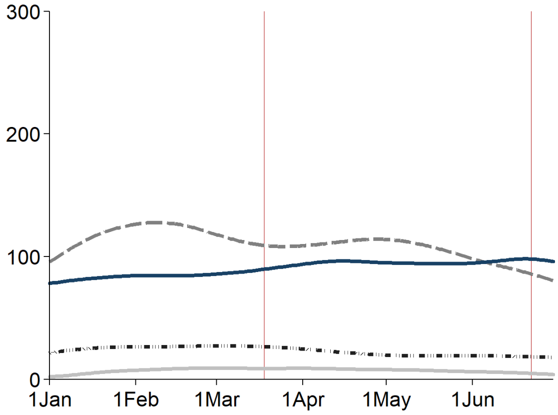
(c) Active user-repos

Figure A30: Belgium's path plot

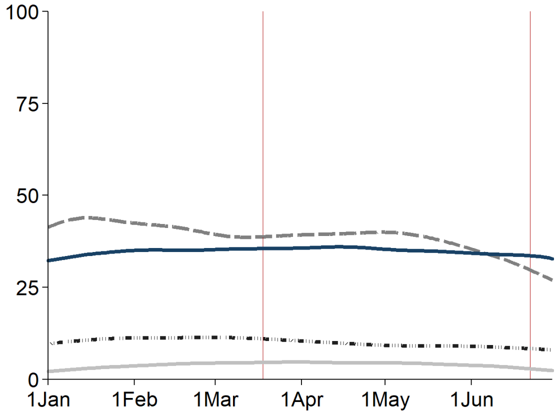
Notes. Path of user activity for those located in Belgium (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). Belgium imposed mandatory WFH for some sectors (WFH = 2) starting March 14, expanded this to all-but-essential workplaces (WFH = 3) on March 18, and then back to mandatory WFH for some sectors on May 11. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



(a) Commits per user-repo



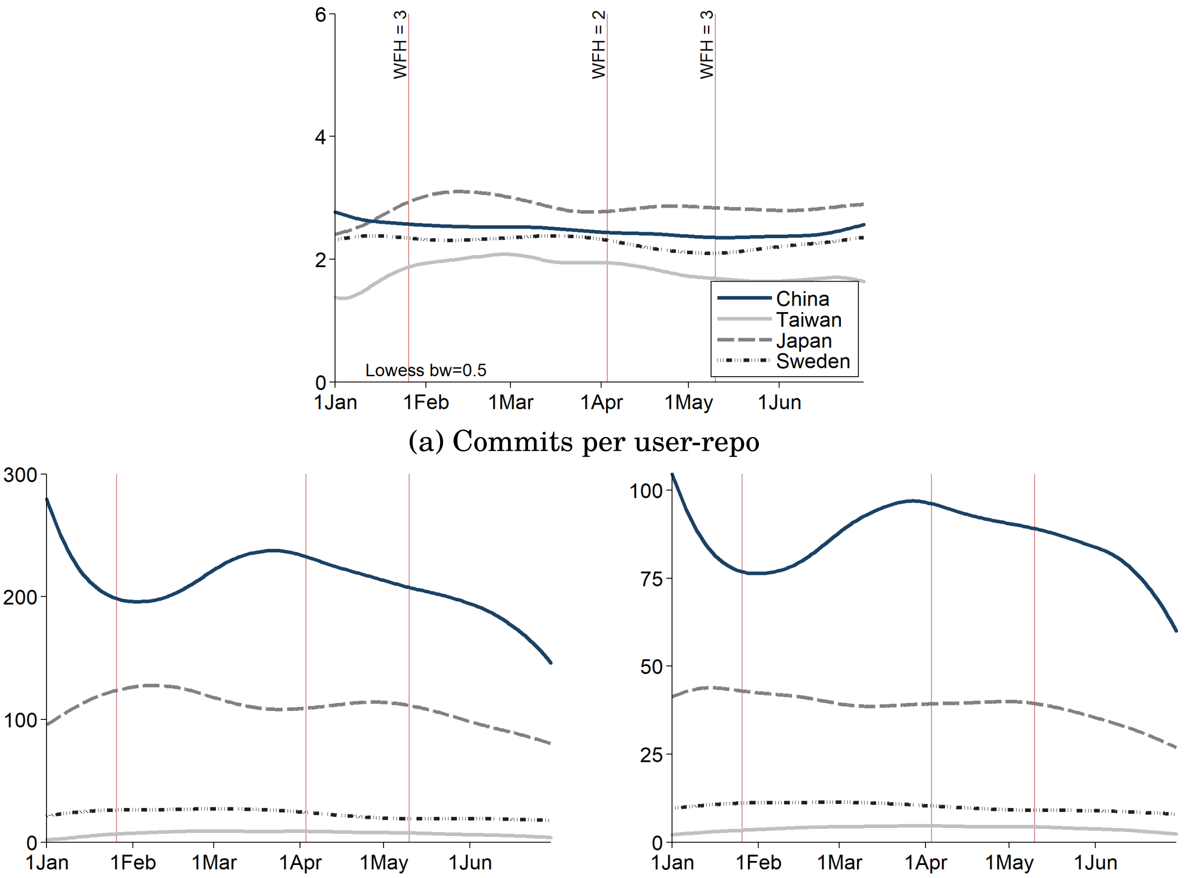
(b) Commits



(c) Active user-repos

Figure A31: Canada's path plot

Notes. Path of user activity for those located in Canada (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). Canada imposed mandatory WFH for all-but-essential workplaces (WFH = 3) on March 18, and then relaxed this to mandatory WFH for some sectors (WFH = 2) starting June 22. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



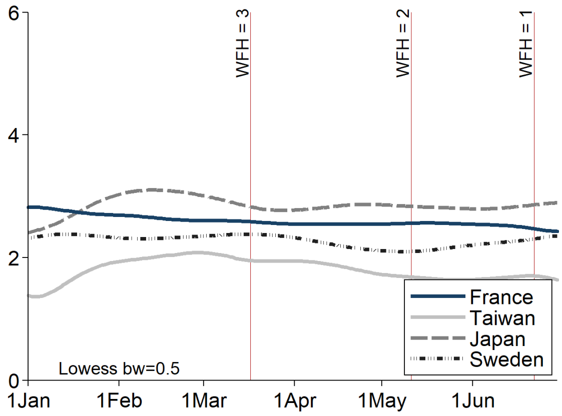
(a) Commits per user-repo

(b) Commits

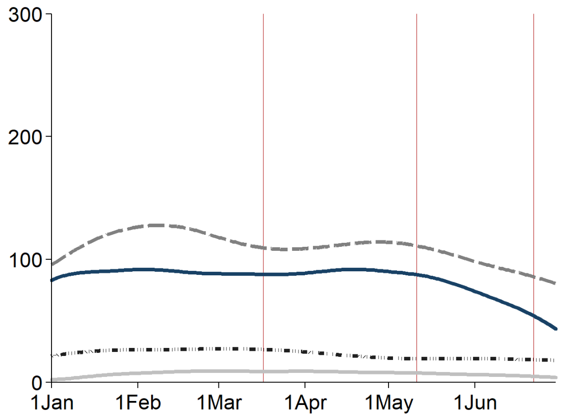
(c) Active user-repos

Figure A32: China's path plot

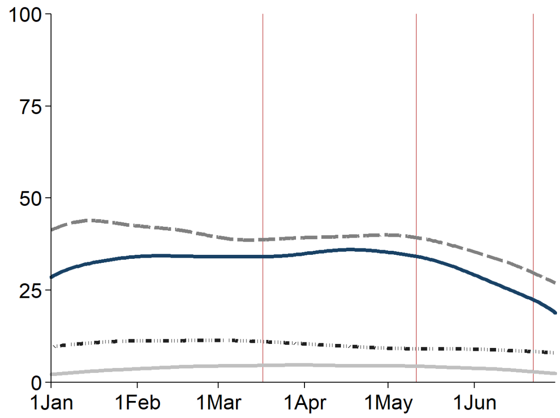
Notes. Path of user activity for those located in China (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). China imposed mandatory WFH for all-but-essential workplaces (WFH = 3) on January 26, relaxed to mandatory WFH for some sectors (WFH = 2) on April 3, and then back to mandatory WFH for all-but-essential workplaces on May 10. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



(a) Commits per user-repo



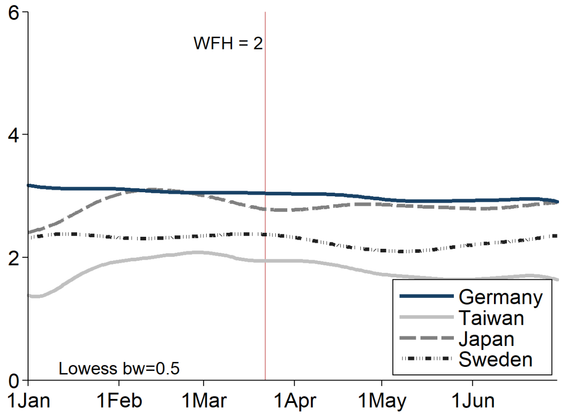
(b) Commits



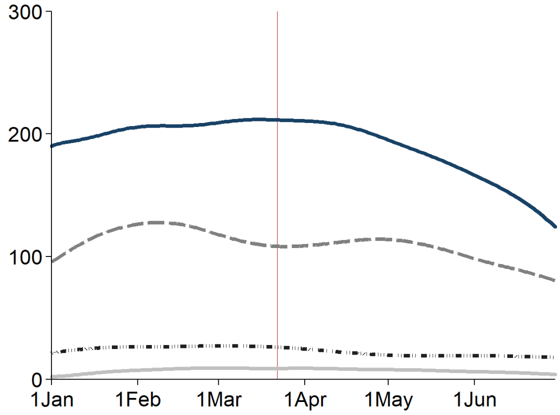
(c) Active user-repos

Figure A33: France's path plot

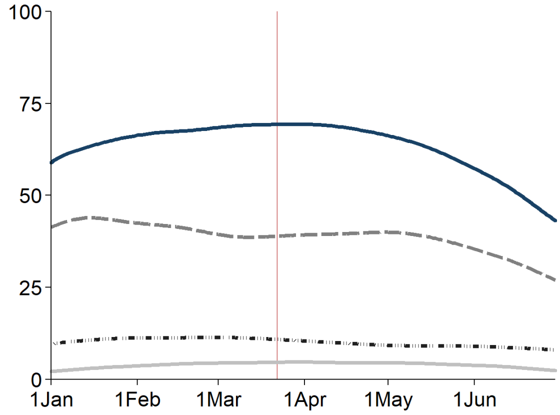
Notes. Path of user activity for those located in France (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). France imposed mandatory WFH for all-but-essential workplaces on March 17, then decreased it to mandatory WFH for some sectors (WFH = 2) on May 11, and finally to a recommended WFH (WFH = 1) on June 22. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



(a) Commits per user-repo



(b) Commits



(c) Active user-repos

Figure A34: Germany's path plot

Notes. Path of user activity for those located in Germany (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). Germany imposed mandatory WFH for some sectors on March 22 (WFH = 2). The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.

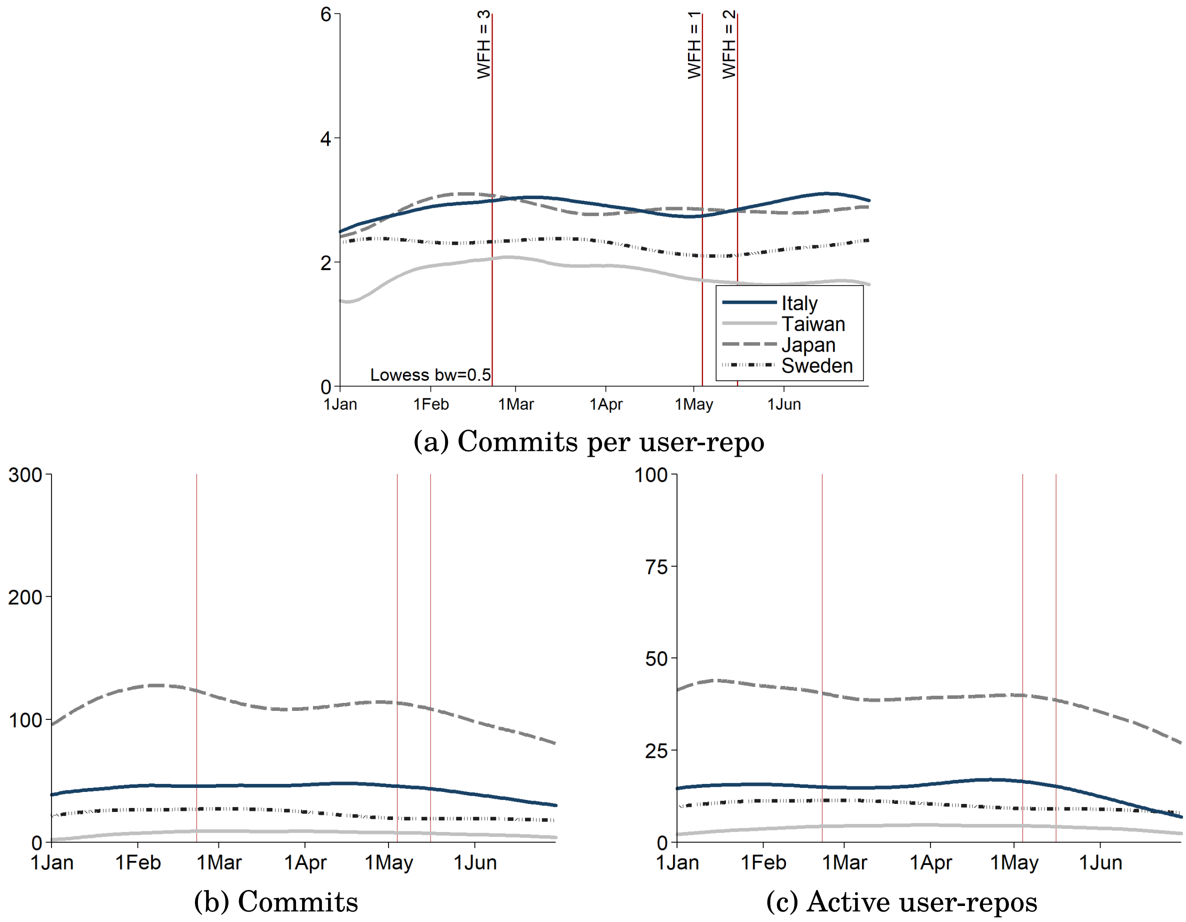
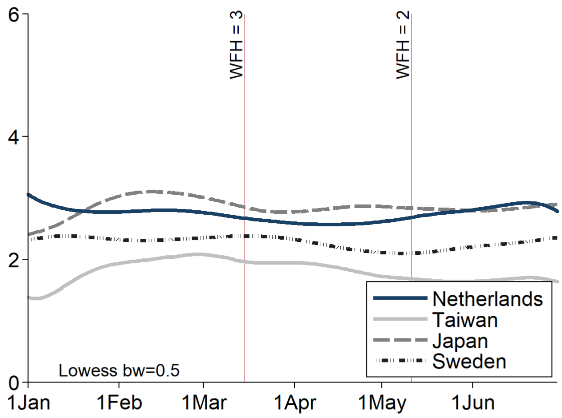
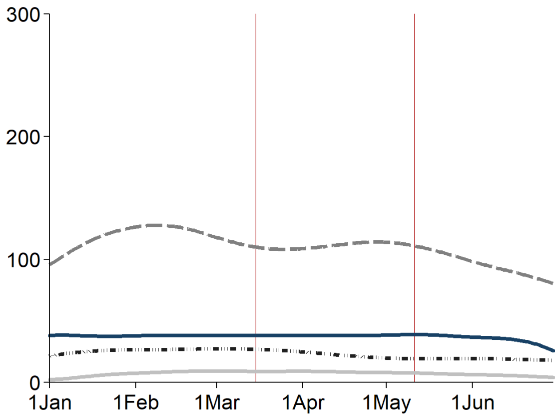


Figure A35: Italy's path plot

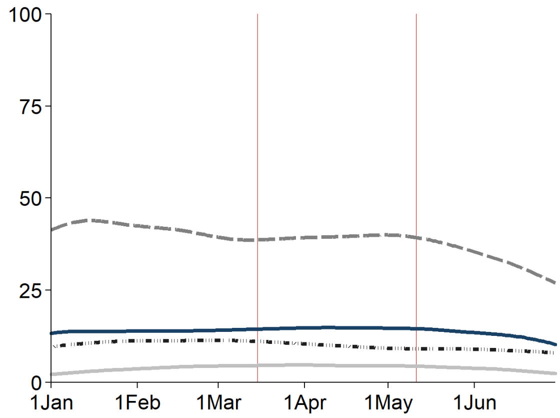
Notes. Path of user activity for those located in Italy (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). Italy imposed mandatory for all-but-essential workplaces (WFH = 3) on February 22, relaxed to recommended WFH (WFH = 1) on May 4, and up again to mandatory WFH for some sectors (WFH = 2) on May 16. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



(a) Commits per user-repo



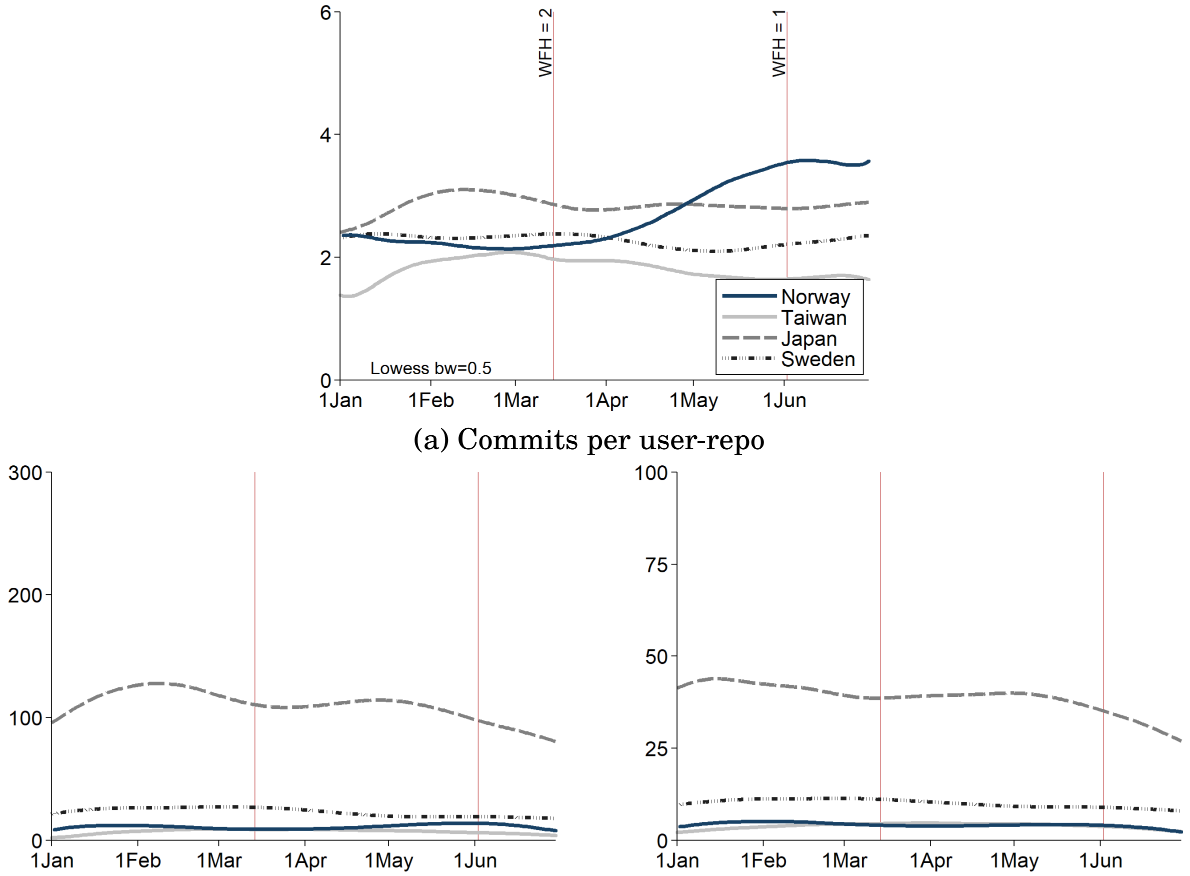
(b) Commits



(c) Active user-repos

Figure A36: Netherlands' path plot

Notes. Path of user activity for those located in Netherlands' (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). Netherlands' imposed mandatory for all-but-essential workplaces (WFH = 3) on March 15, then relaxed to mandatory WFH for some sectors (WFH = 2) on May 11. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



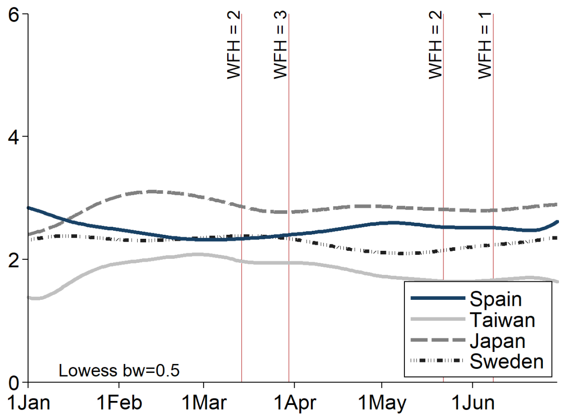
(a) Commits per user-repo

(b) Commits

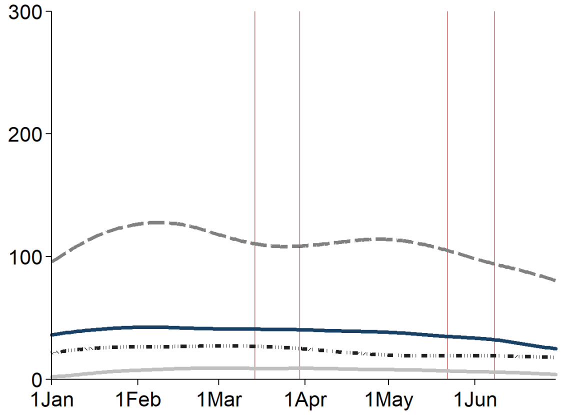
(c) Active user-repos

Figure A37: Norway's path plot

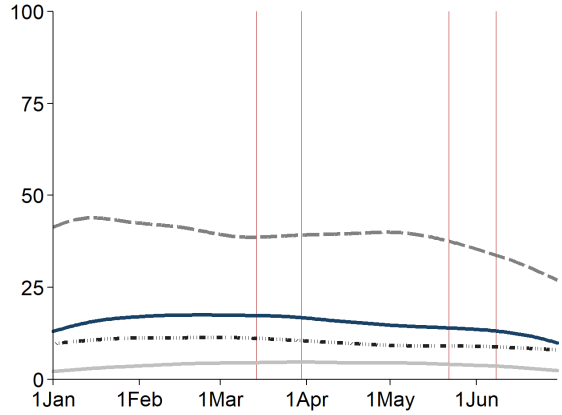
Notes. Path of user activity for those located in Norway (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). Norway imposed mandatory WFH for some sectors (WFH = 2) on March 12, then relaxed to recommended WFH (WFH = 1) on June 2. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



(a) Commits per user-repo



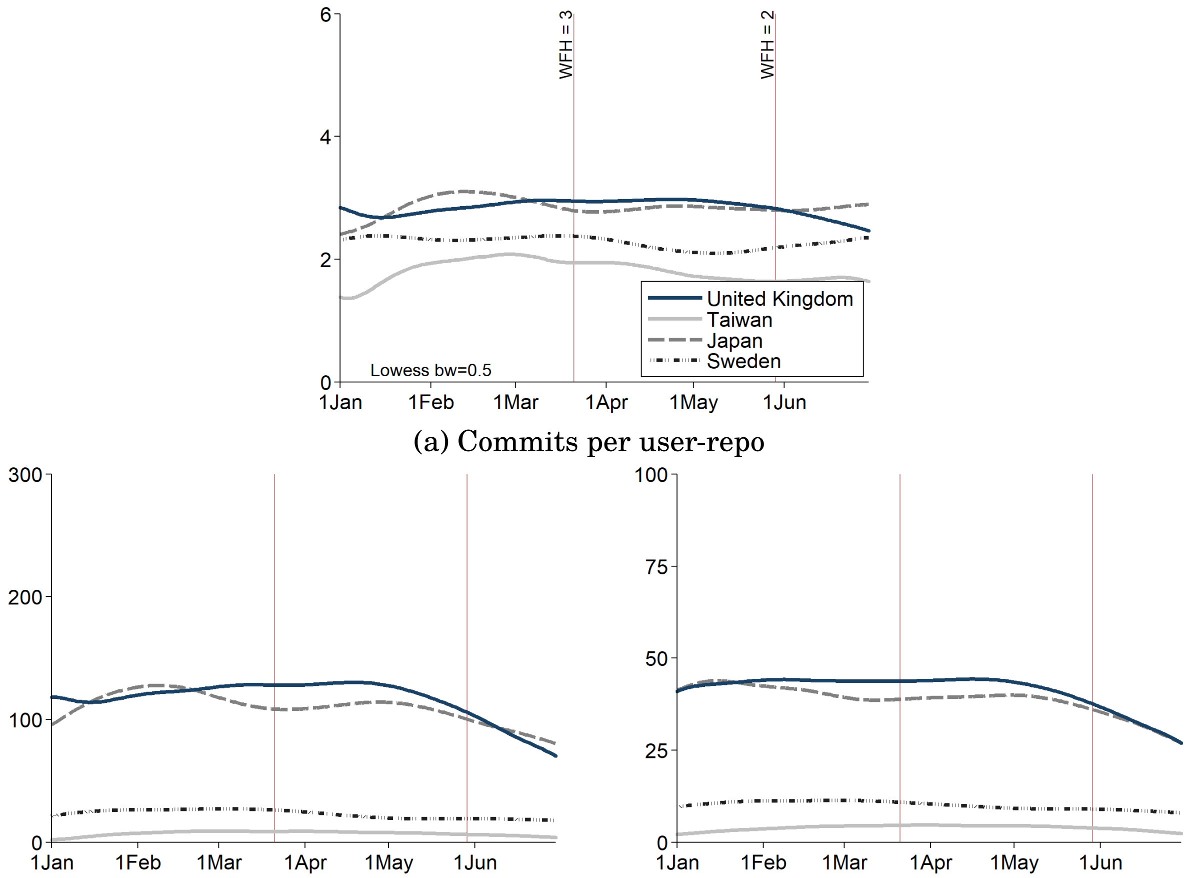
(b) Commits



(c) Active user-repos

Figure A38: Spain's path plot

Notes. Path of user activity for those located in Spain (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). Spain imposed mandatory WFH for some sectors (WFH = 2) on March 14, increased to mandatory for all-but-essential workplaces (WFH = 3) on March 30, then relaxed back to mandatory WFH for some sectors on May 22. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



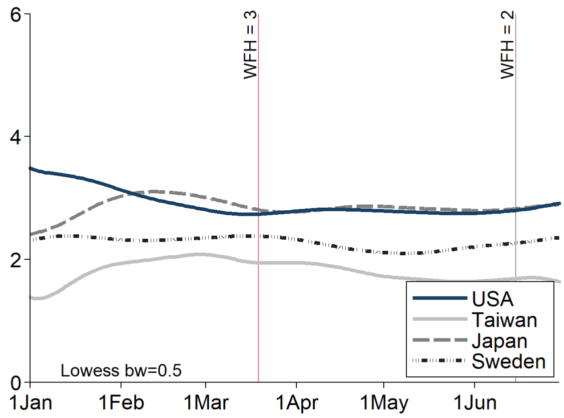
(a) Commits per user-repo

(b) Commits

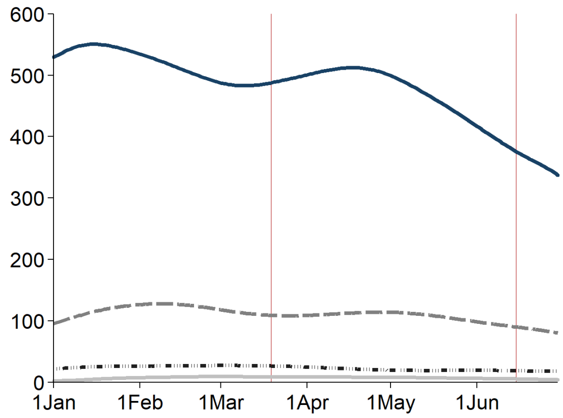
(c) Active user-repos

Figure A39: United Kingdom's path plot

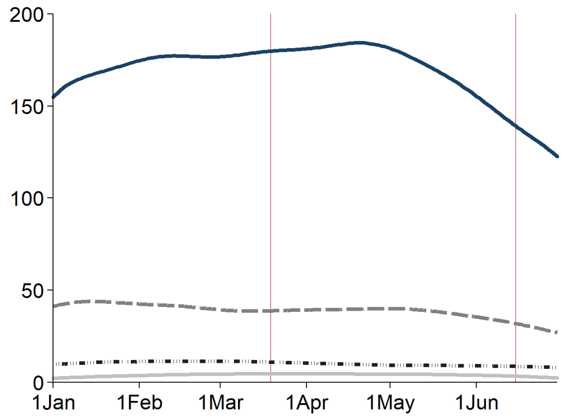
Notes. Path of user activity for those located in United Kingdom (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). United Kingdom imposed mandatory WFH for all-but-essential workplaces (WFH = 3) on March 21, and then relaxed to mandatory WFH for some sectors (WFH = 2) on May 29. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



(a) Commits per user-repo



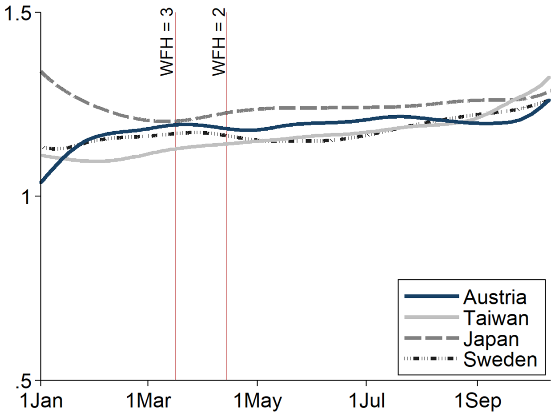
(b) Commits



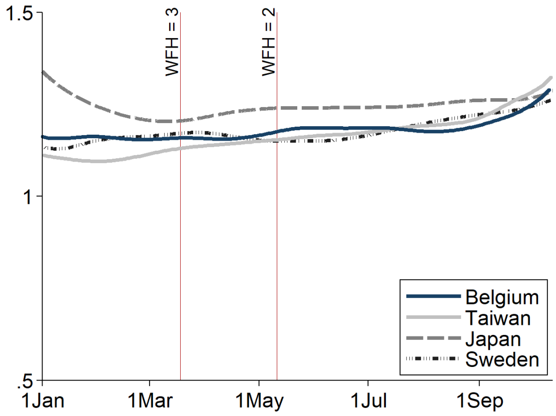
(c) Active user-repos

Figure A40: United States' path plot

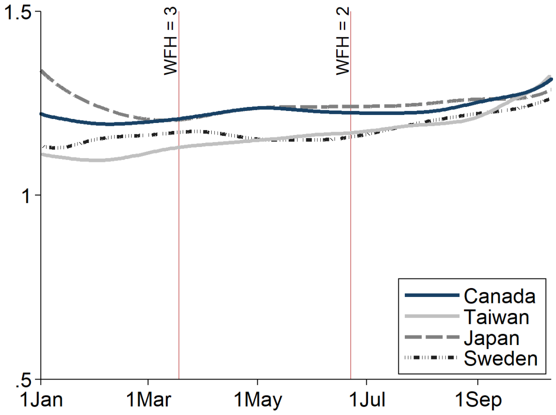
Notes. Path of user activity for those located in the United States (blue solid line), using Lowess smoothing on individual records aggregated up to the daily level.. Values are subfigure (a) is equivalent to values in subfigure (b) divided by values in subfigure (c). The United States imposed mandatory WFH for all-but-essential workplaces (WFH = 3) on March 19, then relaxed to mandatory WFH for some sectors (WFH = 2) on June 15. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



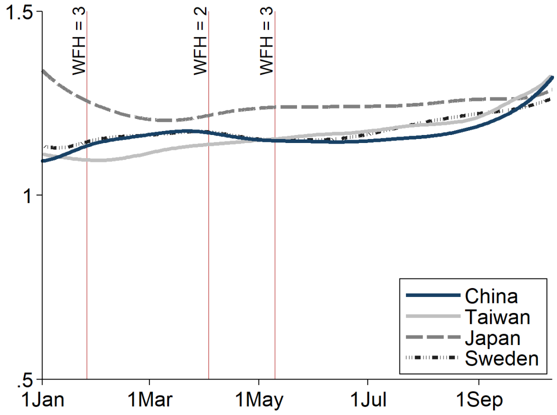
(a) Austria's path plot



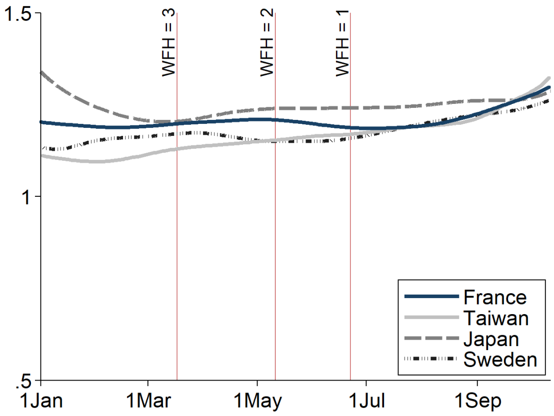
(b) Belgium's path plot



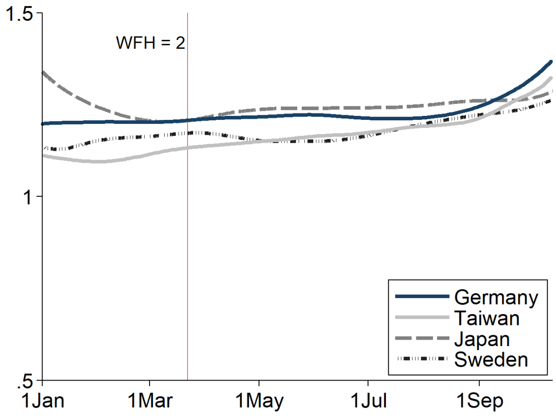
(c) Canada's path plot



(d) China's path plot



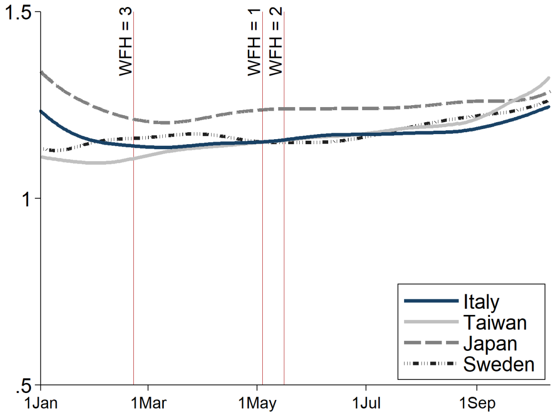
(e) France's path plot



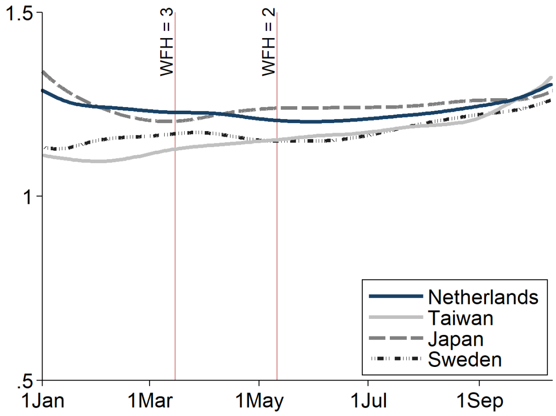
(f) Germany's path plot

Figure A41: Pull requests [part 1]

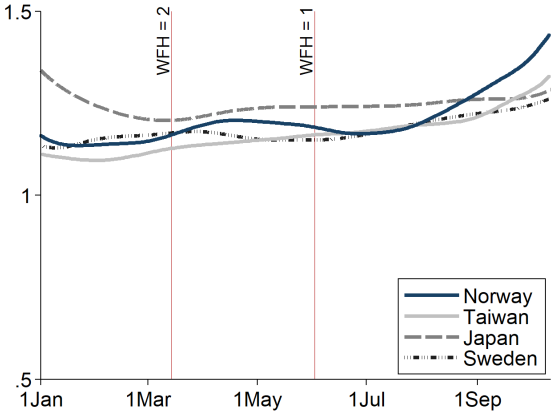
Notes. Path plots of pull requests per user-repo using Lowess smoothing on individual records aggregated up to the daily level. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



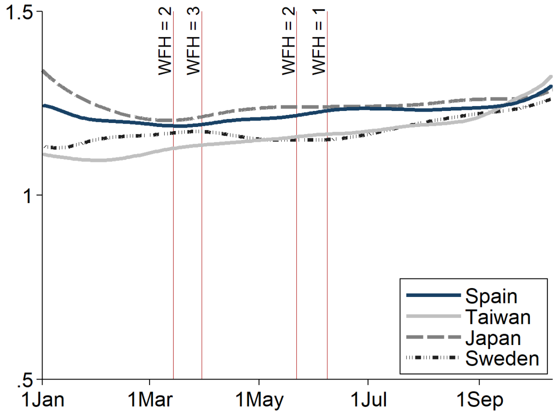
(a) Italy's path plot



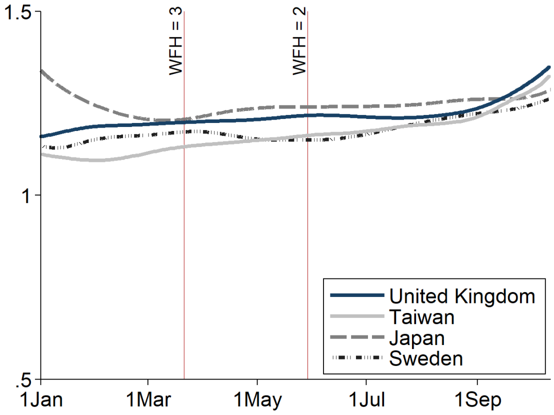
(b) Netherlands' path plot



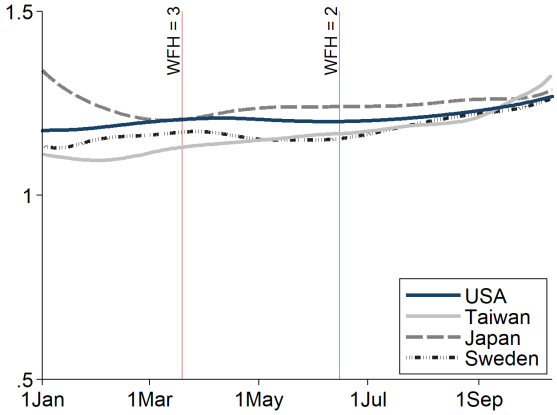
(c) Norway's path plot



(d) Spain's path plot



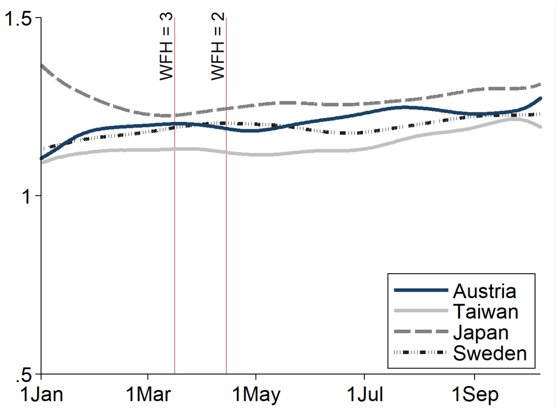
(e) United Kingdom's path plot



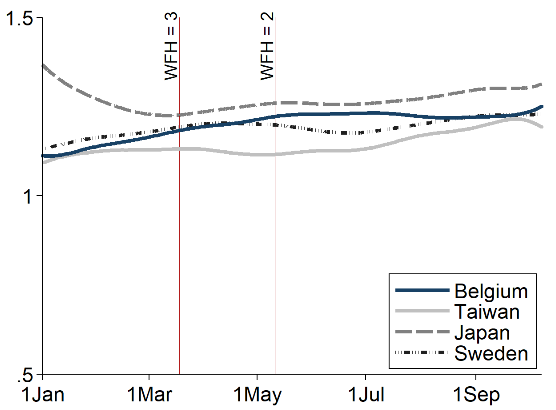
(f) United States' path plot

Figure A42: Pull requests [part 2]

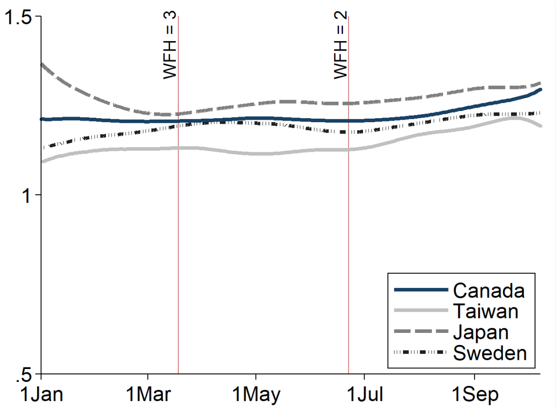
Notes. Path plots of pull requests per user-repo using Lowess smoothing on individual records aggregated up to the daily level. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



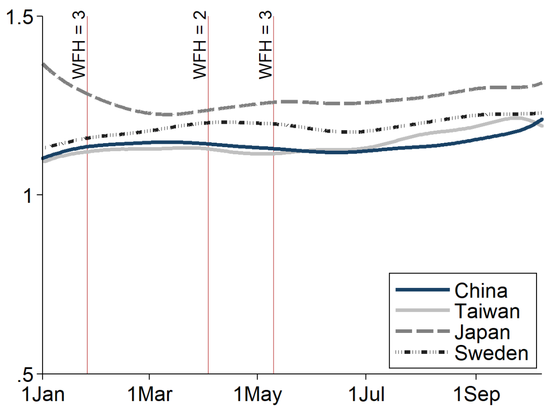
(a) Austria's path plot



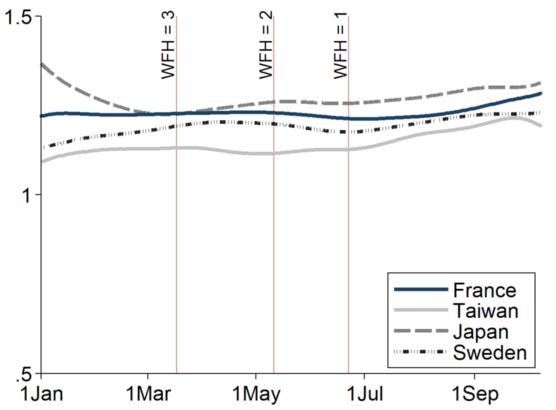
(b) Belgium's path plot



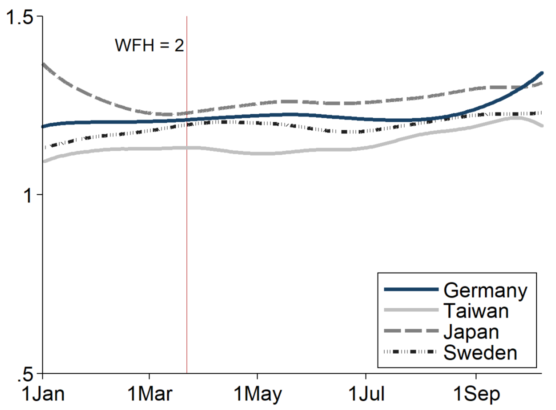
(c) Canada's path plot



(d) China's path plot



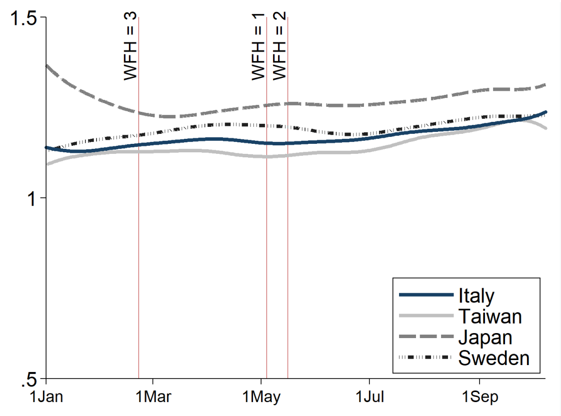
(e) France's path plot



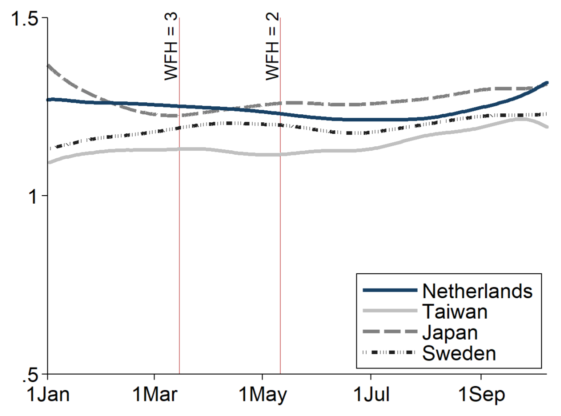
(f) Germany's path plot

Figure A43: Opened issues [part 1]

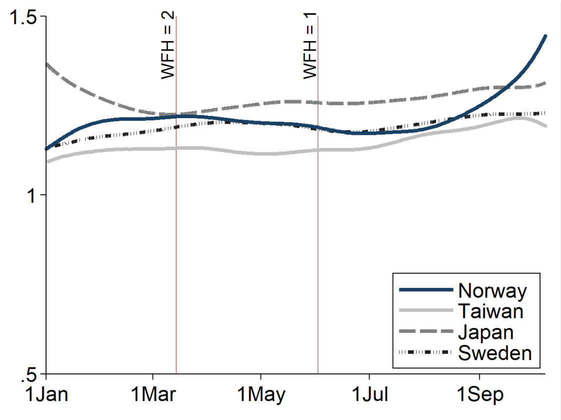
Notes. Path plots of opened issues per user-repo using Lowess smoothing on individual records aggregated up to the daily level. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



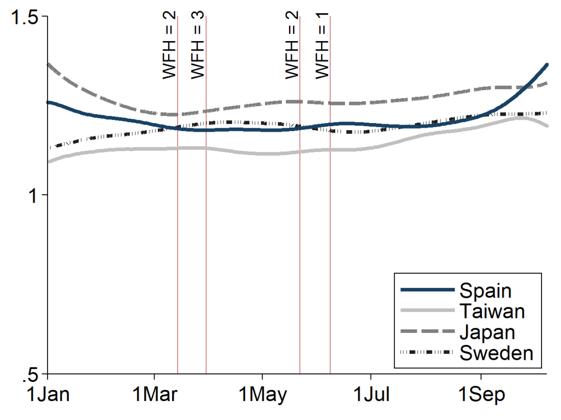
(a) Italy's path plot



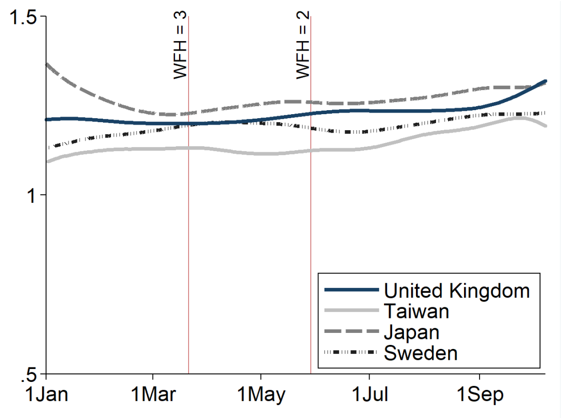
(b) Netherlands' path plot



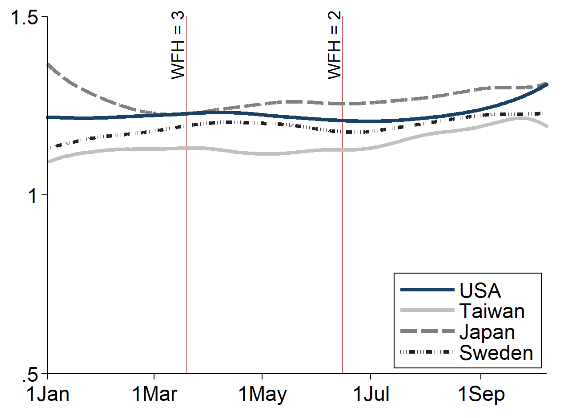
(c) Norway's path plot



(d) Spain's path plot



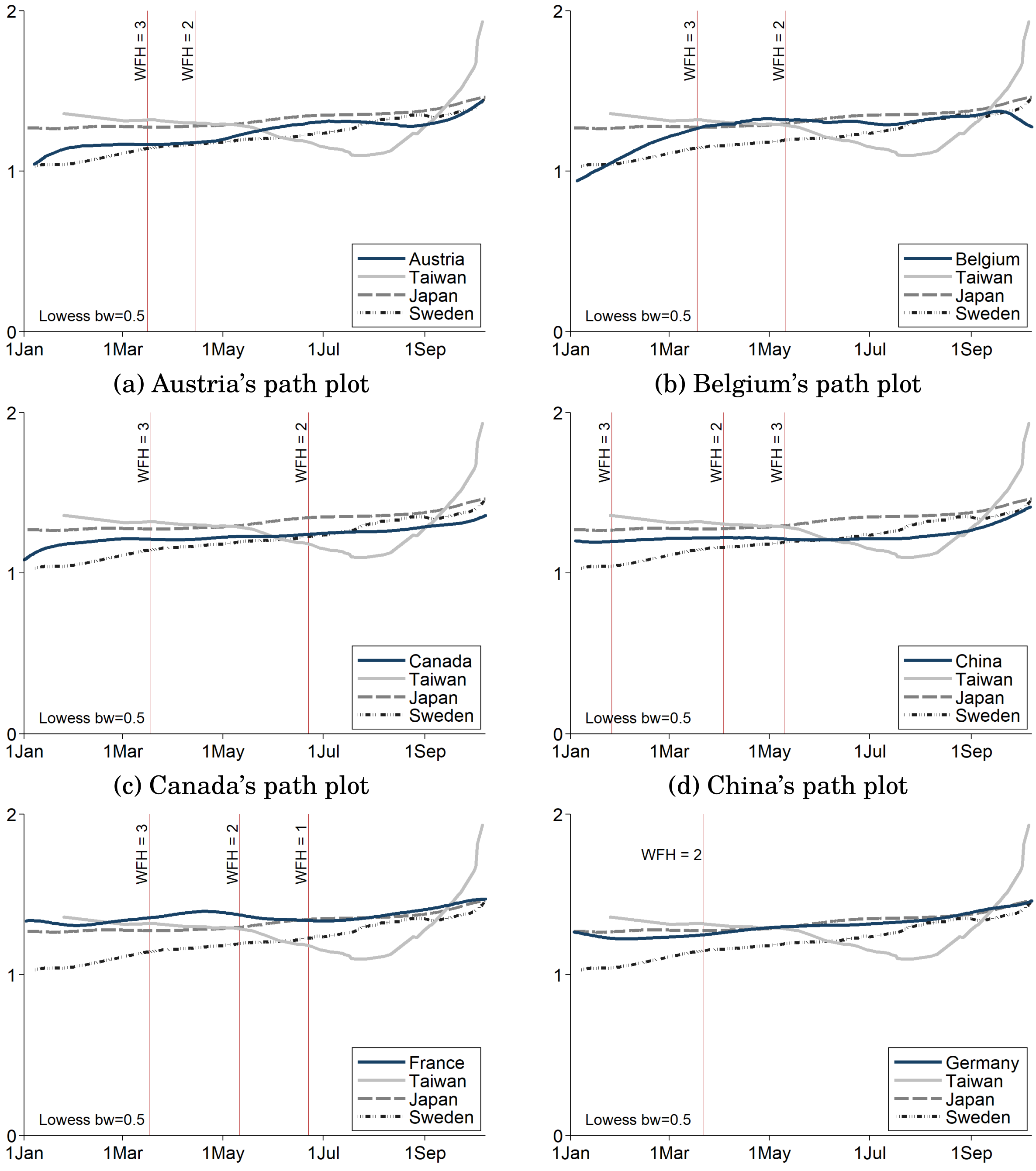
(e) United Kingdom's path plot



(f) United States' path plot

Figure A44: Opened issues [part 2]

Notes. Path plots of opened issues per user-repo using Lowess smoothing on individual records aggregated up to the daily level. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



(a) Austria's path plot

(b) Belgium's path plot

(c) Canada's path plot

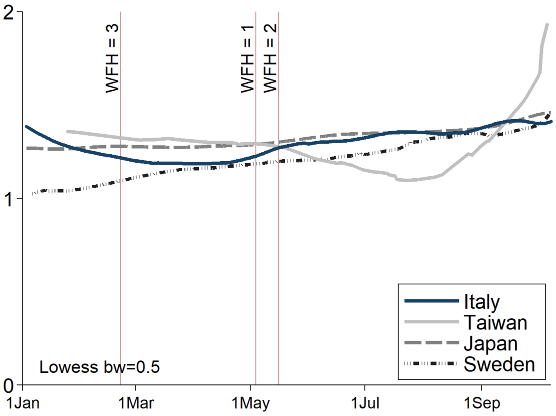
(d) China's path plot

(e) France's path plot

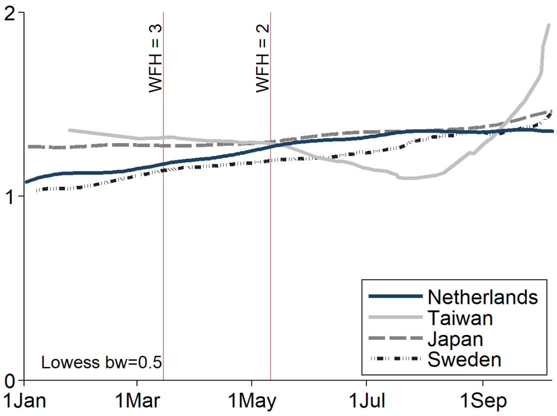
(f) Germany's path plot

Figure A45: Closed issues [part 1]

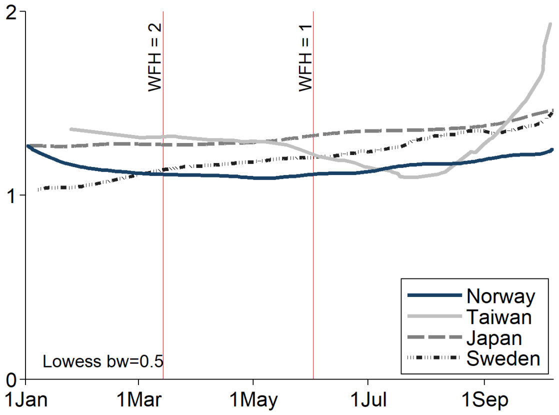
Notes. Path plots of closed issues per user-repo using Lowess smoothing on individual records aggregated up to the daily level. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.



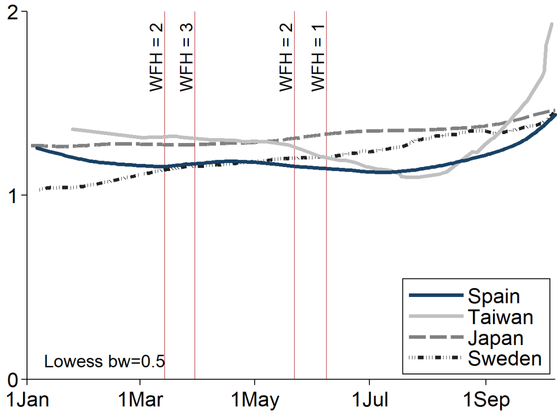
(a) Italy's path plot



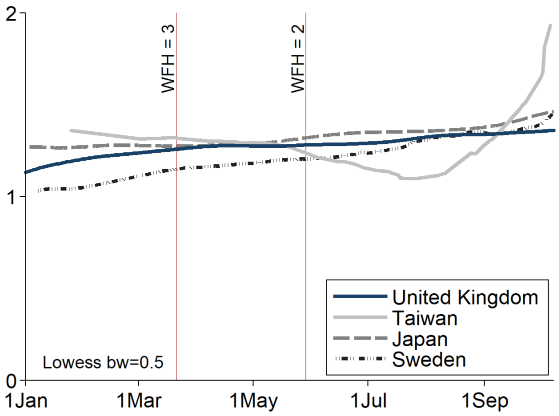
(b) Netherlands' path plot



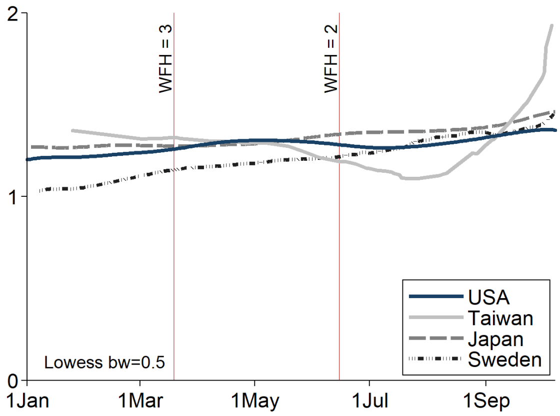
(c) Norway's path plot



(d) Spain's path plot



(e) United Kingdom's path plot



(f) United States' path plot

Figure A46: Closed issues [part 2]

Notes. Path plots of closed issues per user-repo using Lowess smoothing on individual records aggregated up to the daily level. The path of Japan, Sweden, and Taiwan (three notable countries that never imposed mandatory WFH in the commits sample period) are shown in gray as reference. Variables winsorized at 5% and 95%.

E Microsample results (additional figures and tables)

Table A16—*Microsample DID Results (User Level)*

	Dependent variable is			
	Log commits per user-repo-day		Log pull requests per per user-repo-day	
	(1)	(2)	(3)	(4)
$\mathbb{1}^{\text{WFH}=1}$	0.05365***	0.06176***	−0.00818***	−0.01241***
	(0.01944)	(0.02190)	(0.00131)	(0.00218)
$\mathbb{1}^{\text{WFH}=2,3}$	−0.00455	0.00301	−0.00445***	−0.00867***
	(0.00675)	(0.01466)	(0.00091)	(0.00212)
Individual				
$\mathbb{1}^{\text{WFH}>0}$ × Individual age		−0.00030		0.00009
		(0.00046)		(0.00006)
$\mathbb{1}^{\text{WFH}>0}$ × Repositories		0.00257		0.00239
		(0.00467)		(0.00174)
$\mathbb{1}^{\text{WFH}>0}$ × Gists		−0.00967		0.00040***
		(0.00645)		(0.00009)
$\mathbb{1}^{\text{WFH}>0}$ × Followers		0.00017		0.00014
		(0.00148)		(0.00011)
$\mathbb{1}^{\text{WFH}>0}$ × Following		−0.00152*		−0.00018*
		(0.00085)		(0.00009)
$H_a : \mathbb{1}^{\text{WFH}=1} > 0$, p-val	.003***	.003***	1	1
$H_a : \mathbb{1}^{\text{WFH}=2,3} > 0$, p-val	.749	.419	1	1
$H_a : \mathbb{1}^{\text{WFH}=1} < 0$, p-val	.997	.997	0***	0***
$H_a : \mathbb{1}^{\text{WFH}=2,3} < 0$, p-val	.251	.581	0***	0***
Individual fixed effects	Yes	Yes	Yes	Yes
Repository fixed effects	Yes	Yes	Yes	Yes
R^2	.79	.79	.59	.59
Country observations	94	94	102	102
Individual observations	4,981	4,981	10,346	10,346
Repositories observations	.	.	.	.
User-repo-WFH arm observations	12,570	12,570	34,091	34,091

Notes—Table reports the regression coefficients from estimating Equation (2) for the commits microsample (columns (1)–(2)) and for the pull requests sample (columns (3)–(4)). Even-numbered columns include the interaction of the individual and repository characteristics with a dummy that equals one if there is *any* WFH regulation—$\mathbb{1}^{\text{WFH}>0} \times X_{ij}$. In particular, the coefficients of the WFH dummies in the first two rows of the odd- and even-numbered columns corresponds to Figure A51 and Figure A52, respectively. Individual and repository characteristics are divided by 100 for scaling. Standard errors are clustered by countries.

*** Significant at the 1 per cent level.

** Significant at the 5 per cent level.

* Significant at the 10 per cent level.

Table A17—*Microsample DID Results (User-Repository Level)*

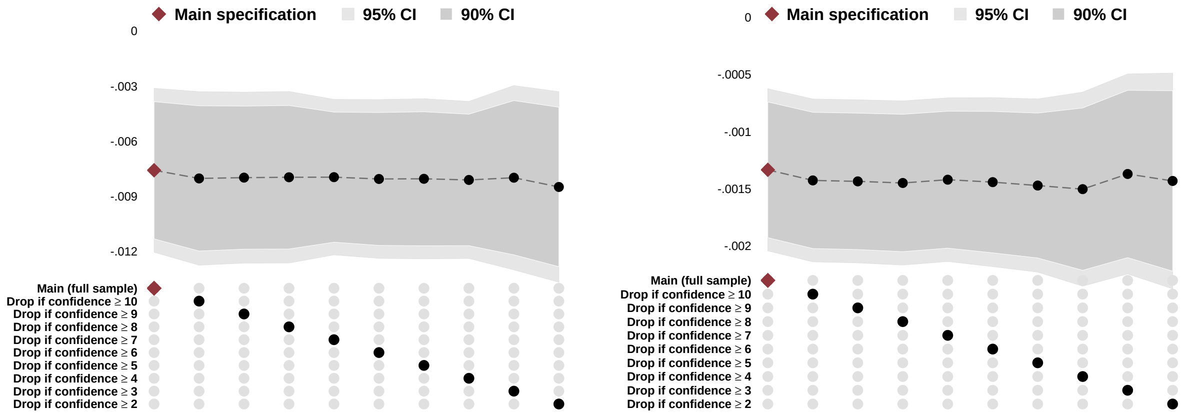
	Dependent variable is			
	Log commits per user-repo-day		Log pull requests per per user-repo-day	
	(1)	(2)	(3)	(4)
$\mathbb{1}^{\text{WFH}=1}$	-0.01643^{***}	-0.01978^{***}	-0.00241^{***}	-0.00935^{***}
	(0.00257)	(0.00702)	(0.00047)	(0.00187)
$\mathbb{1}^{\text{WFH}=2,3}$	-0.00758^{***}	-0.01080	-0.00133^{***}	-0.00829^{***}
	(0.00225)	(0.00727)	(0.00036)	(0.00198)
Individual				
$\mathbb{1}^{\text{WFH}>0}$ × Individual age		-0.00017		0.00010^{*}
		(0.00015)		(0.00005)
$\mathbb{1}^{\text{WFH}>0}$ × Repositories		0.00211		0.00029
		(0.00130)		(0.00018)
$\mathbb{1}^{\text{WFH}>0}$ × Gists		-0.00200		0.00004^{***}
		(0.00186)		(0.00001)
$\mathbb{1}^{\text{WFH}>0}$ × Followers		0.00016		0.00003
		(0.00026)		(0.00002)
$\mathbb{1}^{\text{WFH}>0}$ × Following		-0.00037^{*}		-0.00002
		(0.00021)		(0.00003)
Repository				
$\mathbb{1}^{\text{WFH}>0}$ × Repository age		0.00035		0.00005^{*}
		(0.00024)		(0.00003)
$\mathbb{1}^{\text{WFH}>0}$ × Contributors		0.01095		0.01480^{***}
		(0.01163)		(0.00215)
$\mathbb{1}^{\text{WFH}>0}$ × Contributions (others)		-0.00003^{**}		0.00002^{**}
		(0.00001)		(0.00001)
$\mathbb{1}^{\text{WFH}>0}$ × Stars		-0.00003		-0.00000
		(0.00002)		(0.00000)
$\mathbb{1}^{\text{WFH}>0}$ × Forks		0.00006^{*}		0.00003^{*}
		(0.00004)		(0.00002)
$H_a : \mathbb{1}^{\text{WFH}=1} > 0$, p-val	1	.997	1	1
$H_a : \mathbb{1}^{\text{WFH}=2,3} > 0$, p-val	.999	.93	1	1
$H_a : \mathbb{1}^{\text{WFH}=1} < 0$, p-val	0^{***}	$.003^{***}$	0^{***}	0^{***}
$H_a : \mathbb{1}^{\text{WFH}=2,3} < 0$, p-val	$.001^{***}$	$.07^{*}$	0^{***}	0^{***}
Individual fixed effects	Yes	Yes	Yes	Yes
Repository fixed effects	Yes	Yes	Yes	Yes
R^2	.72	.72	.36	.36
Country observations	117	117	102	102
Individual observations	13,818	13,613	10,346	10,344
Repositories observations	16,840	16,529	24,675	24,671
User-repo-WFH arm observations	63,520	62,565	116,359	116,345

Notes—Table reports the regression coefficients from estimating Equation (2) for the commits microsample (columns (1)–(2)) and for the pull requests sample (columns (3)–(4)). Even-numbered columns include the interaction of the individual and repository characteristics with a dummy that equals one if there is *any* WFH regulation—$\mathbb{1}^{\text{WFH}>0} \times \boldsymbol{X}_{ij}$. In particular, the coefficients of the WFH dummies in the first two rows of the odd- and even-numbered columns corresponds to Figure A51 and Figure A52, respectively. Individual and repository characteristics are divided by 100 for scaling. Standard errors are clustered by countries.

*** Significant at the 1 per cent level.

** Significant at the 5 per cent level.

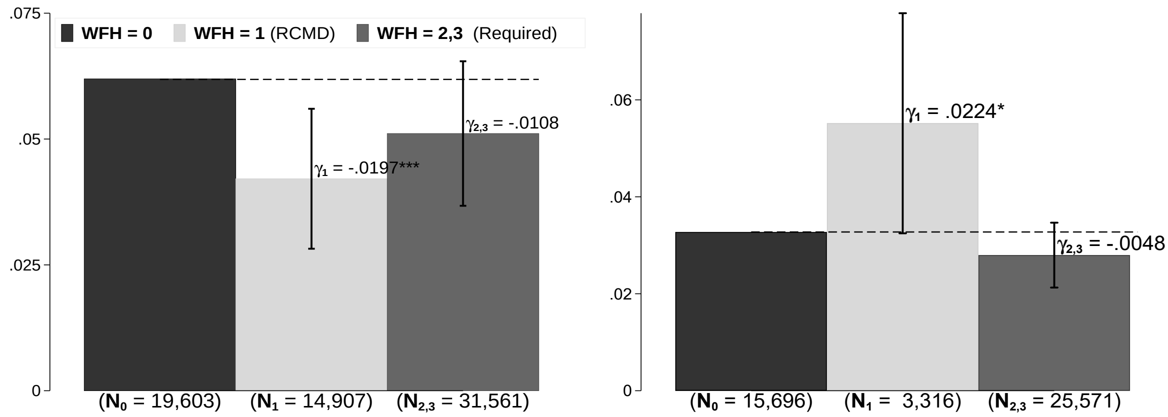
* Significant at the 10 per cent level.



(a) Commits (b) Pulls requests

Figure A47: Sensitivity to Geocoding Confidence

Notes—Plot shows how the required WFH estimates ($\gamma_{2,3}$), from estimating Equation (2) and as reported in the micro-sample results in Figure A51, changes when activities from users that are less confidently matched to regions are progressively dropped from estimation. The "Confidence" number, as returned by the OSM API, *increases* as the API is *less* certain about the geocoded region. This is also corroborated by a random sample of a 1,000 geocodings (see Appendix E in the Online Appendix).



(a) Commits (b) Pull requests

Figure A48: Microsample DID with Controls (balanced)

Notes—Figure plots the estimated impact (estimates of γ_k from Equation (2)) of state-imposed WFH. The dependent variables are commits and pull requests per individual-repository per day in a WFH arm. Similar to Figure A51 but with an additional $\mathbb{1}^{\{\text{OxCGRT WFH}>0\}}$ interaction with the individual and repository characteristics. The first bar in each subfigure indicates the baseline—WFH=0 (no WFH). Subsequent bars add back the estimated impacts to the baseline estimate ($\gamma_0+\gamma_\ell$, $\ell = 1$ or $2,3$). Annotated estimates in figures are the estimates of γ_k. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively. Parenthesized numbers ($\mathbf{N}_k$) below bars indicate size of the individual-repository observations for the corresponding WFH arm. Capped vertical bars are 95% confidence intervals from robust standard errors clustered by country.

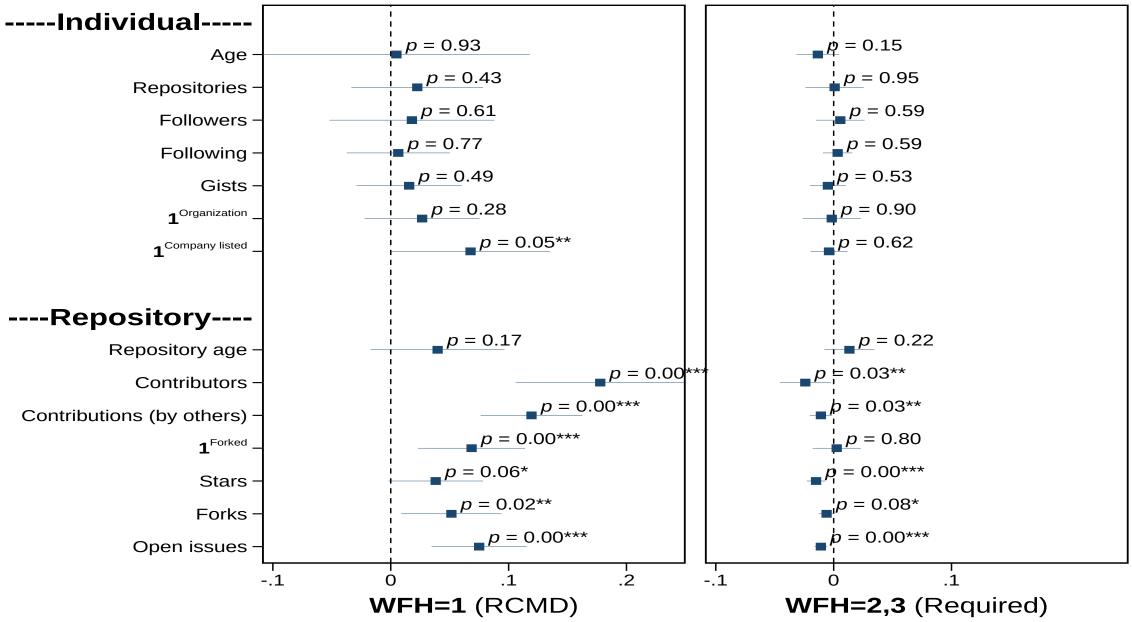


Figure A49: Differences in Observables (Commits)

Notes—Differences in means for WFH=1 (recommended WFH) and WFH=2,3 (required WFH), compared to WFH=0 (no state regulation), using the microsample from the pull requests records. The WFH codings are the OxCGRT codings. Units in standard deviations. Repository age is defined as creation date minus 1 Jan 2020; contributions is total number of commits, pull requests, or number of issues opened; the dummy for forked indicates whether the repository was branched out from a preexisting one; stars is a measure of impact (used as a like or bookmark); forks is the number of branching out by other users; and open issues refers to the number of unresolved issues listed in the project. Tables A5–A6 tabulates the above results. Number of individuals and repositories captured are 76,830 and 72,923, respectively. The individual and repository level observations are clustered by country and programming language, respectively. ***, **, and * denotes significance at the 1, 5, and 10 percent level,

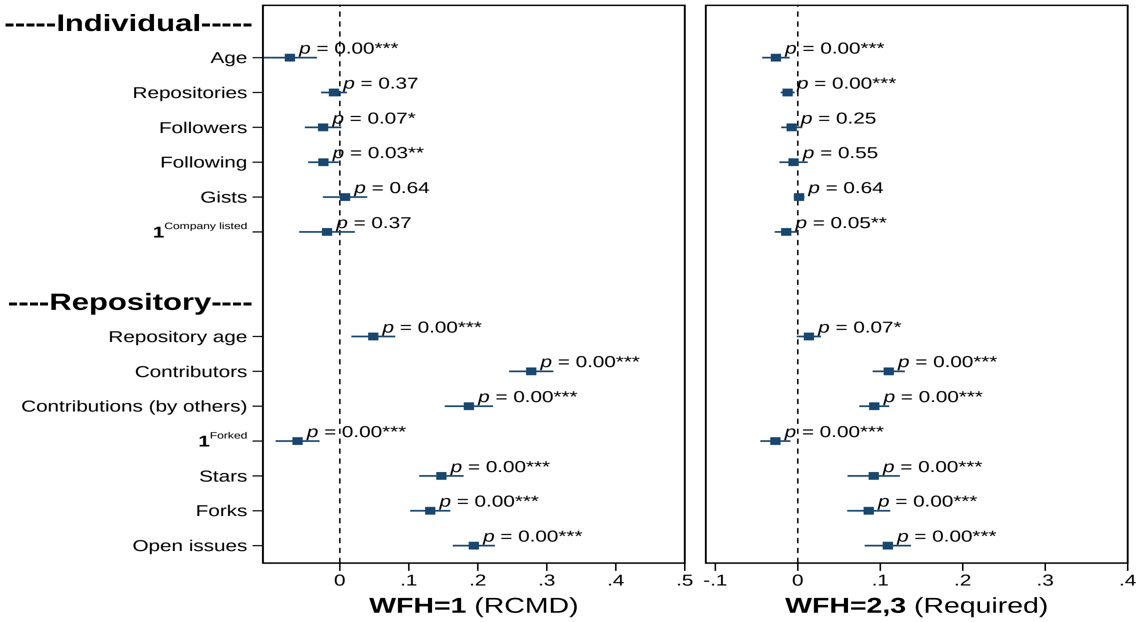
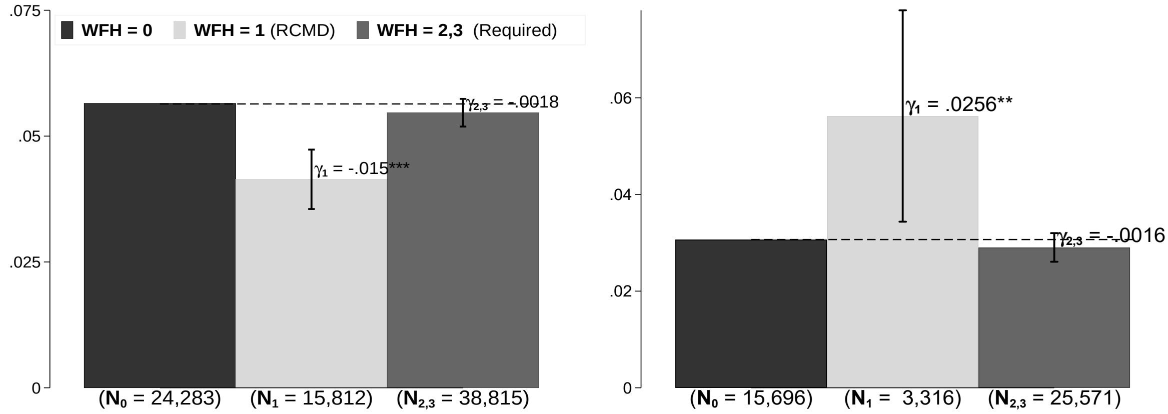


Figure A50: Differences in Observables (Pull Requests)

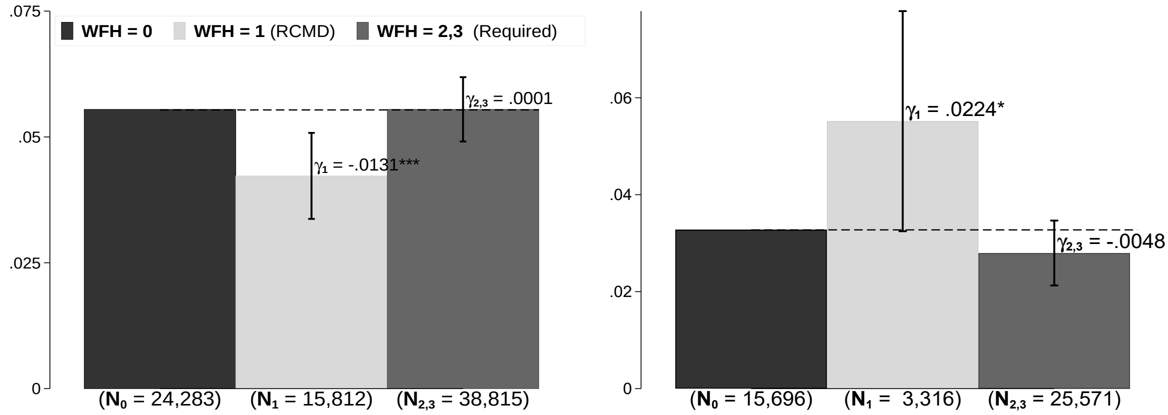
Notes—Differences in means for WFH=1 (recommended WFH) and WFH=2,3 (required WFH), compared to WFH=0 (no state regulation), using the microsample from the pull requests records. The WFH codings are the OxCGRT codings. Units in standard deviations. Repository age is defined as creation date minus 1 Jan 2020; contributions is total number of commits, pull requests, or number of issues opened; the dummy for forked indicates whether the repository was branched out from a preexisting one; stars is a measure of impact (used as a like or bookmark); forks is the number of branching out by other users; and open issues refers to the number of unresolved issues listed in the project. Tables A7–A8 tabulates the above results. Number of individuals and repositories captured are 76,830 and 72,923, respectively. The individual and repository level observations are clustered by country and programming language, respectively. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively.



(a) Commits (b) Pull requests

Figure A51: Microsample DID (Unbalanced)

Notes—Figure plots the estimated impact (estimates of γ_k from Equation (2)) of state-imposed WFH. The dependent variables are commits and pull requests per individual-repository per day in a WFH arm. The first bar in each subfigure indicates the baseline—WFH=0 (no WFH). Subsequent bars add back the estimated impacts to the baseline estimate ($\gamma_0+\gamma_\ell$, $\ell = 1$ or $2, 3$). Annotated estimates in figures are the estimates of γ_k. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively. Parenthesized numbers ($\mathbf{N}_k$) below bars indicate size of the individual-repository observations for the corresponding WFH arm. Capped vertical bars are 95% confidence intervals from robust standard errors clustered by country.



(a) Commits (b) Pull requests

Figure A52: MICROSAMPLE DID WITH CONTROLS (UNBALANCED)

Notes—Figure plots the estimated impact (estimates of γ_k from Equation (2)) of state-imposed WFH. The dependent variables are commits and pull requests per individual-repository per day in a WFH arm. Similar to Figure A51 but with an additional $\mathbb{1}^{\{\text{OxCGRT WFH}>0\}}$ interaction with the individual and repository characteristics. The first bar in each subfigure indicates the baseline—WFH=0 (no WFH). Subsequent bars add back the estimated impacts to the baseline estimate ($\gamma_0+\gamma_\ell$, $\ell = 1$ or $2, 3$). Annotated estimates in figures are the estimates of γ_k. ***, **, and * denotes significance at the 1, 5, and 10 percent level, respectively. Parenthesized numbers ($\mathbf{N}_k$) below bars indicate size of the individual-repository observations for the corresponding WFH arm. Capped vertical bars are 95% confidence intervals from robust standard errors clustered by country.

Table A18—*Microsample DID Results (Unbalanced)*

	Dependent variable is			
	Log commits per user-repo-day		Log pull requests per per user-repo-day	
	(1)	(2)	(3)	(4)
$\mathbb{1}^{\text{WFH}=1}$	-0.01498^{***}	-0.01338^{***}	0.00111^{***}	-0.00072
	(0.00301)	(0.00436)	(0.00040)	(0.00059)
$\mathbb{1}^{\text{WFH}=2,3}$	-0.00175	-0.00017	0.00246^{***}	0.00062
	(0.00140)	(0.00309)	(0.00015)	(0.00059)
Individual				
$\mathbb{1}^{\text{WFH}>0}$ × Individual age		-0.00019^{**}		0.00001
		(0.00009)		(0.00002)
$\mathbb{1}^{\text{WFH}>0}$ × Repositories		0.00116		-0.00005
		(0.00113)		(0.00009)
$\mathbb{1}^{\text{WFH}>0}$ × Gists		-0.00229		-0.00000
		(0.00218)		(0.00000)
$\mathbb{1}^{\text{WFH}>0}$ × Followers		0.00025		0.00002
		(0.00020)		(0.00001)
$\mathbb{1}^{\text{WFH}>0}$ × Following		-0.00035		-0.00004^{*}
		(0.00025)		(0.00002)
Repository				
$\mathbb{1}^{\text{WFH}>0}$ × Repository age		0.00025^{*}		-0.00004^{***}
		(0.00014)		(0.00001)
$\mathbb{1}^{\text{WFH}>0}$ × Contributors		-0.00631		0.01110^{***}
		(0.00718)		(0.00101)
$\mathbb{1}^{\text{WFH}>0}$ × Contributions (others)		-0.00002^{**}		0.00002^{***}
		(0.00001)		(0.00000)
$\mathbb{1}^{\text{WFH}>0}$ × Stars		-0.00001		-0.00000
		(0.00001)		(0.00000)
$\mathbb{1}^{\text{WFH}>0}$ × Forks		0.00004^{**}		0.00001^{*}
		(0.00002)		(0.00001)
$H_a : \mathbb{1}^{\text{WFH}=1} > 0$, p-val	1	.999	$.003^{***}$	.888
$H_a : \mathbb{1}^{\text{WFH}=2,3} > 0$, p-val	.893	.522	0^{***}	.149
$H_a : \mathbb{1}^{\text{WFH}=1} < 0$, p-val	0^{***}	$.001^{***}$	.997	.112
$H_a : \mathbb{1}^{\text{WFH}=2,3} < 0$, p-val	.107	.478	1	.851
Individual fixed effects	Yes	Yes	Yes	Yes
Repository fixed effects	Yes	Yes	Yes	Yes
R^2	.66	.66	.32	.32
Country observations	124	123	143	143
Individual observations	16,092	15,853	62,594	62,590
Repositories observations	18,656	18,311	49,623	49,617
User-repo-WFH arm observations	79,915	78,654	346,878	346,858

Notes—Table reports the regression coefficients from estimating Equation (2) for the commits microsample (columns (1)–(2)) and for the pull requests sample (columns (3)–(4)). Even-numbered columns include the interaction of the individual and repository characteristics with a dummy that equals one if there is *any* WFH regulation—$\mathbb{1}^{\text{WFH}>0} \times \boldsymbol{X}_{ij}$. In particular, the coefficients of the WFH dummies in the first two rows of the odd- and even-numbered columns corresponds to Figure A51 and Figure A52, respectively. Individual and repository characteristics are divided by 100 for scaling. Standard errors are clustered by countries.

*** Significant at the 1 per cent level.

** Significant at the 5 per cent level.

* Significant at the 10 per cent level.

D Geocoding examples

Table A13—Random examples of failed geocoding

Location independent	Bangalore, Remote
Just here on Earth… for now	Jerome Library, BGSU Campus
@ransty	Tokyo, Hangzhou, Canberra
5602 Research Park Blvd, Suite 300, Madison, WI 53719	San Francisco, CA, USA - Paris, FR - Lyon, FR
The Linked Open Data Cloud :-)	Vancouver / SF / NYC
Vilnius/Kybartai, Lithuania	Boujailles - Haut-Doubs - France
Alphabit	SF | NYC | Remote
In your apps	Egypt, Monofeya, Quesna
The Wired | Everywhere	Edinburgh / Berlin
World/Montreal/NYC	Sofia, Montevideo, Tokyo, London, Bangalore, Cranbury
Stuck in a infinite loop	77 Massachusetts Ave, Bldg 37 Room 447, Cambridge, MA 02139
United Nations (OCHA), New York	Moscow + Dessau
Nederland aka The Netherlands	Greater Boston area, Massachusetts
Home - where I work from.	Greater New York Area; Tulsa, OK
Paris, Thailand, Hong Kong	Potland, OR, USA
In your website	Toronto, New York City, Boston, Portland
Shanghai,mainland China	London/Berlin/Oxford
Leiden / The Hague / Utrecht, The Netherlands	3900 W Alameda Ave, Suite 1200, Burbank CA
Belgium, Netherlands, Romania, Germany, Austria, Italy, Czech Republic	幻ちょあ郷
Dallas, Texas, USA, 3rd Rock, Sol, …	Virgo Super-Cluster, Universe
Somewhere in northern Italy	Greater New York City Area, USA
UoN Towers, 12th Floor; Nairobi, Kenya	Snodak
San Francisco, CA & Boston, MA	Detroit - Graz - Mainz
Pennsylvania State University, University Park, PA	relocating to Europe
Toulouse, Paris, Grenoble, everywhere	Non Euclidean Hellscape

Table A14—Random sample of 100 confidence=1 samples (100% accuracy)

Location string	Geocoded country	Geocoded state
Bangkok, Thailand.	Thailand	
Serres, Greece	Greece	Αποκεντρωμένη Διοίκηση Μακεδονίας - Θράκης
SuZhou, JiangSu	China	江苏省
Sorocaba/São Paulo/Brasil	Brazil	São Paulo
izmir, Turkey	Turkey	—
Brazil, Rio Grande do Sul	Brazil	Rio Grande do Sul
china	China	—
Salzburg, Austria	Austria	Salzburg
Itu/SP	Brazil	São Paulo
Russia, Kirov	Russian Federation	Кировская область
Warsaw (Poland)	Poland	województwo mazowieckie
London,UK	United Kingdom	England
Izmir / Turkey	Turkey	—
chengdu, sichuan	China	四川省
武汉, CN	China	湖北省
Venezia / Italy	Italy	Veneto
Santa Rosa, CA, USA	United States of America	California
Jia Ding,Shang Hai	China	上海市
NYC, NY US	United States of America	New York
Calgary, Alberta	Canada	Alberta
Houston, USA	United States of America	Texas
Medan, Indonesia	Indonesia	Sumatera Utara
Ciudad de México	Mexico	Ciudad de México
DAEJEON, Republic of Korea	Korea, Republic of	—
near Frankfurt, Germany	Germany	Hessen
Canton Province, China	China	广东省
Austin, TX	United States of America	Texas
Phoenix Arizona US	United States of America	Arizona
Campinas - SP - Brazil	Brazil	São Paulo
Linz / Austria	Austria	Oberösterreich
Asturias	Spain	Asturias / Asturies
Malatya	Turkey	Malatya
Bulgaria	Bulgaria	—
Shenyang City,Liaoning Province,China	China	辽宁省
Israel.	Israel	—
INDIA	India	—
Toyota, Aichi Japan.	Japan	—
Medan	Indonesia	Sumatera Utara
Nicaragua	Nicaragua	—
Republic of Belarus	Belarus	—
Montreal / QC - Canada	Canada	Québec
Recife - PE - Brazil	Brazil	Pernambuco
Thuringia, Germany	Germany	Thüringen
Campinas, SP - Brazil	Brazil	São Paulo
Kashiwa, Japan	Japan	—
West Cork, Ireland	Ireland	—
Boise, Idaho USA	United States of America	Idaho
New Orleans, USA	United States of America	Louisiana
San Jose CA	United States of America	California
Hangzhou, Zhejiang, China	China	浙江省
Mayenne (France)	France	Pays de la Loire
Ourense (Galicia)	Spain	Galicia / Galiza
ChaoAn	China	广东省
Boston, Mass	United States of America	Massachusetts
İzmir / Turkey	Turkey	—
Jaipur, Rajasthan, India	India	Rajasthan
Miskolc, Hungary	Hungary	—
Germany	Germany	—
Vigo (Spain)	Spain	Galicia / Galiza
Toronto ON, Canada	Canada	Ontario
Des Moines„ IA	United States of America	Iowa
Braga, Portugal	Portugal	Norte
Cape Town - SA	South Africa	Western Cape
Kiev/Ukraine	Ukraine	—
重庆	China	重庆市
north america	—	—
Morelia, Mexico	Mexico	Michoacán de Ocampo
Castellón, Spain	Spain	Comunitat Valenciana
Kingsville, Ontario	Canada	Ontario

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Table A14 – Continued from previous page

Location string	Geocoded country	Geocoded state
The UK	United Kingdom	—
Toowoomba, Australia	Australia	Queensland
São Paulo/SP - BR	Brazil	São Paulo
Philippines	Philippines	—
Squamish, BC, Canada	Canada	British Columbia
Hang Zhou	China	浙江省
China Zhejiang Shaoxing	China	浙江省
buenos aires	Argentina	—
La Paz, Bolivia	Bolivia (Plurinational State of)	La Paz
Mazatlan, Mexico	Mexico	Sinaloa
Porto Alegre, RS - Brazil	Brazil	Rio Grande do Sul
Santa Fe	Argentina	Santa Fe
Washington, D.C.	United States of America	District of Columbia
Berlin Area, Germany	Germany	—
São Paulo/SP - Brasil	Brazil	São Paulo
San Francisco Bay Area, California, USA	United States of America	California
Valais, Switzerland	Switzerland	Valais/Wallis
Saint Petersburg, Russia	Russian Federation	Санкт-Петербург
Winston-Salem, NC	United States of America	North Carolina
Taipei (Taiwan)	Taiwan, Province of China	臺北市
Praia Grande / São Paulo / Brasil	Brazil	São Paulo
Spain - Valencia	Spain	Comunitat Valenciana
Saigon, Vietnam	Viet Nam	—
NL	Netherlands	—
Suzhou, Jiangsu, China	China	江苏省
Tulsa, OK	United States of America	Oklahoma
NJ USA	United States of America	New Jersey
Joinville, SC, Brazil	Brazil	Santa Catarina
Salvador, Bahia - Brasil	Brazil	Bahia
Denver, Co	United States of America	Colorado
Kursk, Russia	Russian Federation	Курская область

Table A15—Random sample of 100 confidence=2 samples (100% accuracy)

Location string	Geocoded country	Geocoded state
Paris, TX	United States of America	Texas
Lafayette, Louisiana, USA	United States of America	Louisiana
South Bend, Indiana	United States of America	Indiana
Rzeszów, Poland	Poland	województwo podkarpackie
Mainz & Köln	Germany	Rheinland-Pfalz
Treves (Germany)	Germany	Rheinland-Pfalz
Murrieta, CA	United States of America	California
Ivanovo, Russia	Russian Federation	Ивановская область
Paris (France)	France	Île-de-France
Cruz das Almas	Brazil	Bahia
Baltimore, Maryland, USA	United States of America	Maryland
Sioux Falls, SD	United States of America	South Dakota
Skopje, Macedonia	North Macedonia	Скопски СР
Caloocan City	Philippines	—
Namur, Belgium	Belgium	Wallonie
Rochester, Ny	United States of America	New York
Las Palmas De Gran Canaria	Spain	—
Paris	France	Île-de-France
Manchester, NH	United States of America	New Hampshire
brooklyn, new york	United States of America	New York
Tuebingen, Germany	Germany	Baden-Württemberg
Nampa, Idaho	United States of America	Idaho
Miami, Fl	United States of America	Florida
Kawagoe, Japan	Japan	—
Redlands, California, USA	United States of America	California
New Smyrna Beach, FL USA	United States of America	Florida
Pittsburgh, Pennsylvania	United States of America	Pennsylvania
Farmington, NM	United States of America	New Mexico
General Trias, Cavite	Philippines	Cavite
Göttingen	Germany	Niedersachsen
Hsinchu, Taiwan	Taiwan, Province of China	臺灣省
Feira Nova - PE	Brazil	Pernambuco
Santa Barbara	United States of America	California
The Hague, Netherlands	Netherlands	Zuid-Holland
Lugano	Switzerland	Ticino
Italy - Milano	Italy	Lombardia
Palo Alto, CA US	United States of America	California
Tangerang Selatan, Indonesia	Indonesia	Banten
Santa Barbara, USA	United States of America	California
Miami, Florida	United States of America	Florida
Rybinsk	Russian Federation	Ярославская область
Barcelona (SPAIN)	Spain	Catalunya
Pittsburgh, Pa	United States of America	Pennsylvania
Miami, FL. USA	United States of America	Florida
Rzeszow, Poland	Poland	województwo podkarpackie
Moldova, Chisinau	Moldova, Republic of	—
Liverpool, England	United Kingdom	England
Cheyenne, WY	United States of America	Wyoming
Weiden in der Oberpfalz, Germany	Germany	Bayern
Milan area, Italy	Italy	Lombardia
Barcelona	Spain	Catalunya
Melbourne, FL	United States of America	Florida
Osnabrück	Germany	Niedersachsen
Lewiston, ME	United States of America	Maine
Moncton, NB	Canada	New Brunswick
Rabat	Morocco	—
Palo Alto CA, USA	United States of America	California
Deventer, Netherlands	Netherlands	Overijssel
Enschede, The Netherlands	Netherlands	Overijssel
Milano (IT)	Italy	Lombardia
Funabashi, Japan	Japan	—
Redlands, CA	United States of America	California
Saint-Etienne, France	France	Auvergne-Rhône-Alpes
Winsen (Luhe)	Germany	Niedersachsen
Pittsburgh,PA, USA	United States of America	Pennsylvania
Salford, Greater Manchester	United Kingdom	England

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Table A15 – Continued from previous page

Location string	Geocoded country	Geocoded state
Nordhausen	Germany	Thüringen
Hague	Netherlands	Zuid-Holland
Milano - Italy	Italy	Lombardia
Palo Alto	United States of America	California
SeongNam city	Korea, Republic of	—
Turin, Italy	Italy	Piemonte
pittsburgh, pa	United States of America	Pennsylvania
Newcastle, UK	United Kingdom	England
Horten	Norway	—
Pegnitz, Germany	Germany	Bayern
Germany / Bochum	Germany	Nordrhein-Westfalen
Paris area, France	France	Île-de-France
Zwolle	Netherlands	Overijssel
Germany, Kaiserslautern	Germany	Rheinland-Pfalz
Minneapolis,MN	United States of America	Minnesota
Mönchengladbach, Germany	Germany	Nordrhein-Westfalen
Douglasville, GA, USA	United States of America	Georgia
Clovis, CA	United States of America	California
Las Palmas, Spain	Spain	—
Skopje, North Macedonia	North Macedonia	Скопски СР
The Hague, NL	Netherlands	Zuid-Holland
Eugene, OR, 97405, USA	United States of America	Oregon
Annecy, France	France	Auvergne-Rhône-Alpes
Ahaus, DE	Germany	Nordrhein-Westfalen
Miami, FL, USA	United States of America	Florida
Russian Federation Sarov	Russian Federation	Нижегородская область
Mönchengladbach	Germany	Nordrhein-Westfalen
Eugene Oregon	United States of America	Oregon
Maribor, Slovenia	Slovenia	—
Ås, Norway	Norway	—
Bristol, UK	United Kingdom	England
Limoges	France	Nouvelle-Aquitaine
Decatur, IL 62521	United States of America	Illinois
Paris, France	France	Île-de-France

Table A16—Random sample of 100 confidence=2 samples (100% accuracy)

Location string	Geocoded country	Geocoded state
Paris, TX	United States of America	Texas
Lafayette, Louisiana, USA	United States of America	Louisiana
South Bend, Indiana	United States of America	Indiana
Rzeszów, Poland	Poland	województwo podkarpackie
Mainz & Köln	Germany	Rheinland-Pfalz
Treves (Germany)	Germany	Rheinland-Pfalz
Murrieta, CA	United States of America	California
Ivanovo, Russia	Russian Federation	Ивановская область
Paris (France)	France	Île-de-France
Cruz das Almas	Brazil	Bahia
Baltimore, Maryland, USA	United States of America	Maryland
Sioux Falls, SD	United States of America	South Dakota
Skopje, Macedonia	North Macedonia	Скопски СР
Caloocan City	Philippines	—
Namur, Belgium	Belgium	Wallonie
Rochester, Ny	United States of America	New York
Las Palmas De Gran Canaria	Spain	—
Paris	France	Île-de-France
Manchester, NH	United States of America	New Hampshire
brooklyn, new york	United States of America	New York
Tuebingen, Germany	Germany	Baden-Württemberg
Nampa, Idaho	United States of America	Idaho
Miami, Fl	United States of America	Florida
Kawagoe, Japan	Japan	—
Redlands, California, USA	United States of America	California
New Smyrna Beach, FL USA	United States of America	Florida
Pittsburgh, Pennsylvania	United States of America	Pennsylvania
Farmington, NM	United States of America	New Mexico
General Trias, Cavite	Philippines	Cavite
Göttingen	Germany	Niedersachsen
Hsinchu, Taiwan	Taiwan, Province of China	臺灣省
Feira Nova - PE	Brazil	Pernambuco
Santa Barbara	United States of America	California
The Hague, Netherlands	Netherlands	Zuid-Holland
Lugano	Switzerland	Ticino
Italy - Milano	Italy	Lombardia
Palo Alto, CA US	United States of America	California
Tangerang Selatan, Indonesia	Indonesia	Banten
Santa Barbara, USA	United States of America	California
Miami, Florida	United States of America	Florida
Rybinsk	Russian Federation	Ярославская область
Barcelona (SPAIN)	Spain	Catalunya
Pittsburgh, Pa	United States of America	Pennsylvania
Miami, FL. USA	United States of America	Florida
Rzeszow, Poland	Poland	województwo podkarpackie
Moldova, Chisinau	Moldova, Republic of	—
Liverpool, England	United Kingdom	England
Cheyenne, WY	United States of America	Wyoming
Weiden in der Oberpfalz, Germany	Germany	Bayern
Milan area, Italy	Italy	Lombardia
Barcelona	Spain	Catalunya
Melbourne, FL	United States of America	Florida
Osnabrück	Germany	Niedersachsen
Lewiston, ME	United States of America	Maine
Moncton, NB	Canada	New Brunswick
Rabat	Morocco	—
Palo Alto CA, USA	United States of America	California
Deventer, Netherlands	Netherlands	Overijssel
Enschede, The Netherlands	Netherlands	Overijssel
Milano (IT)	Italy	Lombardia
Funabashi, Japan	Japan	—
Redlands, CA	United States of America	California
Saint-Etienne, France	France	Auvergne-Rhône-Alpes
Winsen (Luhe)	Germany	Niedersachsen
Pittsburgh,PA, USA	United States of America	Pennsylvania
Salford, Greater Manchester	United Kingdom	England

Continued on next page

Table A16 – Continued from previous page

Location string	Geocoded country	Geocoded state
Nordhausen	Germany	Thüringen
Hague	Netherlands	Zuid-Holland
Milano - Italy	Italy	Lombardia
Palo Alto	United States of America	California
SeongNam city	Korea, Republic of	—
Turin, Italy	Italy	Piemonte
pittsburgh, pa	United States of America	Pennsylvania
Newcastle, UK	United Kingdom	England
Horten	Norway	—
Pegnitz, Germany	Germany	Bayern
Germany / Bochum	Germany	Nordrhein-Westfalen
Paris area, France	France	Île-de-France
Zwolle	Netherlands	Overijssel
Germany, Kaiserslautern	Germany	Rheinland-Pfalz
Minneapolis,MN	United States of America	Minnesota
Mönchengladbach, Germany	Germany	Nordrhein-Westfalen
Douglasville, GA, USA	United States of America	Georgia
Clovis, CA	United States of America	California
Las Palmas, Spain	Spain	—
Skopje, North Macedonia	North Macedonia	Скопски СР
The Hague, NL	Netherlands	Zuid-Holland
Eugene, OR, 97405, USA	United States of America	Oregon
Annecy, France	France	Auvergne-Rhône-Alpes
Ahaus, DE	Germany	Nordrhein-Westfalen
Miami, FL, USA	United States of America	Florida
Russian Federation Sarov	Russian Federation	Нижегородская область
Mönchengladbach	Germany	Nordrhein-Westfalen
Eugene Oregon	United States of America	Oregon
Maribor, Slovenia	Slovenia	—
Ås, Norway	Norway	—
Bristol, UK	United Kingdom	England
Limoges	France	Nouvelle-Aquitaine
Decatur, IL 62521	United States of America	Illinois
Paris, France	France	Île-de-France

Table A17—Random sample of 100 confidence=3 samples (100% accuracy)

Location string	Geocoded country	Geocoded state
Udine, Italy	Italy	Friuli Venezia Giulia
Fürth, Germany	Germany	Bayern
Latvija, Liepaja	Latvia	Kurzeme
Fareham	United Kingdom	England
Tychy, Poland	Poland	województwo śląskie
Tempe, AZ, USA	United States of America	Arizona
Sankt Veit an der Glan, Austria	Austria	Kärnten
Menlo Park, CA	United States of America	California
Kalamazoo, Michigan, USA	United States of America	Michigan
Stillwater, Oklahoma	United States of America	Oklahoma
St. Paul, Minnesota	United States of America	Minnesota
Den Bosch, Netherlands	Netherlands	Noord-Brabant
Goshen, CT	United States of America	Connecticut
firenze,Italy	Italy	Toscana
Bemidji, MN	United States of America	Minnesota
Russia, Gorno-Altaisk	Russian Federation	Республика Алтай
Lafayette, IN	United States of America	Indiana
Stupino, Russia	Russian Federation	Московская область
Nottingham, U.K.	United Kingdom	England
Kherson, Ukraine	Ukraine	Херсонська область
Liège	Belgium	Wallonie
Amersfoort, Nederland	Netherlands	Utrecht
Lommel	Belgium	Vlaanderen
Canoas, RS, Brazil.	Brazil	Rio Grande do Sul
Pirna	Germany	Sachsen
Zürich, Zurich, Switzerland	Switzerland	Zürich
NANTES	France	Pays de la Loire
Rehau / Germany	Germany	Bayern
Eindhoven, NL	Netherlands	Noord-Brabant
Roanoke, Virginia, USA	United States of America	Virginia
Coburg, Germany	Germany	Bayern
Walla Walla, WA	United States of America	Washington
Bloomington, Illinois	United States of America	Illinois
Klamath Falls, OR	United States of America	Oregon
Tel-Aviv	Israel	מחוז תל אביב
Nijmegen - The Netherlands	Netherlands	Gelderland
Fort Lauderdale, FL, United States	United States of America	Florida
Salem NH	United States of America	New Hampshire
Manhattan, KS, USA	United States of America	Kansas
Utrecht Area, The Netherlands	Netherlands	Utrecht
Nantes (France)	France	Pays de la Loire
Azov	Russian Federation	Ростовская область
Idaho Falls	United States of America	Idaho
Saint Paul, MN, USA	United States of America	Minnesota
Lorgues	France	Provence-Alpes-Côte d'Azur
Syracuse, NY, USA	United States of America	New York
Winterthur	Switzerland	Zürich
Mission Viejo	United States of America	California
Rolla, MO	United States of America	Missouri
Nijmegen. The Netherlands	Netherlands	Gelderland
Penticton, British Columbia, Canada	Canada	British Columbia
St-Germain en Laye, France	France	Île-de-France
Hof	Germany	Bayern
Freyung, Germany	Germany	Bayern
Redwood City, CA	United States of America	California
Vinhedo, Brazil	Brazil	São Paulo
Boulder	United States of America	Colorado
Hradec Králové	Czechia	Severovýchod
Ruston, Louisiana	United States of America	Louisiana
Manhattan, KS	United States of America	Kansas
Cahors, France	France	Occitanie
Croatia, Čakovec	Croatia	—
DeLand, Florida	United States of America	Florida
Vancouver, BC, Canada	Canada	British Columbia
Vancouver, B.C.	Canada	British Columbia
bozeman, MT	United States of America	Montana

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Table A17 – Continued from previous page

Location string	Geocoded country	Geocoded state
Longmont, Co	United States of America	Colorado
Tarnowskie Góry / Poland	Poland	województwo śląskie
New Haven, CT	United States of America	Connecticut
Livermore, CA, USA	United States of America	California
Rovereto (TN), IT	Italy	Trentino-Alto Adige/Südtirol
Willich	Germany	Nordrhein-Westfalen
Fairbanks, Alaska	United States of America	Alaska
St Paul, MN	United States of America	Minnesota
Barueri - SP	Brazil	São Paulo
Pasadena, California	United States of America	California
Menlo Park, California	United States of America	California
Wayne NJ USA	United States of America	New Jersey
Roanoke, VA	United States of America	Virginia
Lausanne (CH)	Switzerland	Vaud
Glendale, CA	Canada	—
Osasco, São Paulo - Brazil	Brazil	São Paulo
Slidell, LA	United States of America	Louisiana
Gießen	Germany	Hessen
Morges, CH	Switzerland	Vaud
Saint-Saturnin-les-Apt, France	France	Provence-Alpes-Côte d'Azur
Israel, Tel Aviv	Israel	מחוז תל אביב
上海市普陀区	China	上海市
Ann Arbor, MI, United States	United States of America	Michigan
Groton, MA	United States of America	Massachusetts
Garner, NC	United States of America	North Carolina
Havant, UK	United Kingdom	England
Narashino, Chiba	Japan	—
Norwell, MA	United States of America	Massachusetts
The Netherlands, Eindhoven	Netherlands	Noord-Brabant
Hollywood, FL	United States of America	Florida
Versmold, Germany	Germany	Nordrhein-Westfalen
Germany, Bad Reichenhall	Germany	Bayern
Gießen, Germany	Germany	Hessen
würzburg, germany	Germany	Bayern

Table A18—Random sample of 100, confidence=4 (99% accuracy)

Location string	Geocoded country	Geocoded state
Austria, Vorarlberg, Dornbirn	Austria	Vorarlberg
Harrisburg, PA	United States of America	Pennsylvania
Hemer, Germany	Germany	Nordrhein-Westfalen
Esporles, Spain	Spain	Illes Balears
The Sun	**France**	**Bretagne**
Åseda, Sweden	Sweden	Kronobergs län
Manassas, VA, USA	United States of America	Virginia
Essen, Antwerp, Belgium	Belgium	Vlaanderen
Dijon, Bourgogne, France	France	Bourgogne-Franche-Comté
Almada, Portugal	Portugal	Área Metropolitana de Lisboa
Flensburg, Germany	Germany	Schleswig-Holstein
Ismaning, Germany	Germany	Bayern
Murter	Croatia	—
North Richland Hills, Texas, USA	United States of America	Texas
DE-27252 Schwaförden	Germany	Niedersachsen
Frankenthal	Germany	Rheinland-Pfalz
Comox, BC, Canada	Canada	British Columbia
Providence, Rhode Island, USA	United States of America	Rhode Island
Eichstätt, Germany	Germany	Bayern
Centerville, OH	United States of America	Ohio
Wolverhampton, UK	United Kingdom	England
Newbury, UK	United Kingdom	England
Killorglin, Ireland	Ireland	—
Fürstenfeldbruck, Germany	Germany	Bayern
Olympia Washington	United States of America	Washington
La Jolla, CA	United States of America	California
Hartford, CT US	United States of America	Connecticut
Broxbourne	United Kingdom	England
Marlow, UK	United Kingdom	England
Brussels, BE	Belgium	Région de Bruxelles-Capitale - Brussels Hoofdstedelijk Gewest
Best, The Netherlands	Netherlands	Noord-Brabant
Foster City	United States of America	California
Lake Forest	United States of America	Illinois
Reston,VA	United States of America	Virginia
Waltham, MA, USA	United States of America	Massachusetts
Mirfield, United Kingdom	United Kingdom	England
France (Lyon)	France	Auvergne-Rhône-Alpes
Peachland, BC	Canada	British Columbia
Posadas, Misiones, Argentina	Argentina	Misiones
Albany, Oregon	United States of America	Oregon
Solon, OH	United States of America	Ohio
Hilversum, Netherlands	Netherlands	Noord-Holland
Bluffdale, UT	United States of America	Utah
Bad Oldesloe, Germany	Germany	Schleswig-Holstein
Princeton, New Jersey, USA	United States of America	New Jersey
lorient, france	France	Bretagne
American Fork, Utah	United States of America	Utah
Saint-Basile-le-Grand, Québec, Canada	Canada	Québec
Apple Valley,MN	United States of America	Minnesota
Montabaur, Germany	Germany	Rheinland-Pfalz
Slough	United Kingdom	England
Darlington, England	United Kingdom	England
Leusden, The Netherlands	Netherlands	Utrecht
Benesov	Czechia	Střední Čechy
Olympia, WA	United States of America	Washington
Wilmington	United States of America	Delaware
Russia, Snezhinsk	Russian Federation	Челябинская область
38547 Calberlah	Germany	Niedersachsen
Johnston, RI	United States of America	Rhode Island
Gaithersburg, MD	United States of America	Maryland
Redondo Beach, CA, USA	United States of America	California
Luserna San Giovanni (TO), Italy	Italy	Piemonte
Sammamish, WA USA	United States of America	Washington
Redmond WA, USA	United States of America	Washington
Alpharetta, GA	United States of America	Georgia
Gibraltar	Gibraltar	Gibraltar
Steamboat Springs, Colorado	United States of America	Colorado
Chur, Switzerland	Switzerland	Graubünden/Grigioni/Grischun
Randolph, NJ	United States of America	New Jersey

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Table A18 – Continued from previous page

Location string	Geocoded country	Geocoded state
Aberystwyth	United Kingdom	Cymru / Wales
Saint Augustine, FL, USA	United States of America	Florida
France, Pau	France	Nouvelle-Aquitaine
Burbank, CA	United States of America	California
Melbourne Australia	Australia	Victoria
Redmond, USA	United States of America	Washington
Saint Augustine, FL	United States of America	Florida
Foster City, CA	United States of America	California
Split, Croatia	Croatia	—
Glen Burnie, MD	United States of America	Maryland
Heemskerk, Netherlands	Netherlands	Noord-Holland
Cambridge, UK	United Kingdom	England
Falconara Marittima AN - Italy	Italy	Marche
Corvallis, Oregon, USA	United States of America	Oregon
West Lafayette, Indiana	United States of America	Indiana
Rome, NY	United States of America	New York
Irpin, Kyiv, Ukraine	Ukraine	Київська область
Maidenhead, UK	United Kingdom	England
Mâcon, France	France	Bourgogne-Franche-Comté
Orinda, California	United States of America	California
Bethesda, MD	United States of America	Maryland
Farnborough, Hampshire, United Kingdom	United Kingdom	England
Berkeley, CA, USA	United States of America	California
Redmond, WA, US	United States of America	Washington
Goirle, The Netherlands	Netherlands	Noord-Brabant
france,Toulon	France	Provence-Alpes-Côte d'Azur
Kaysville, UT	United States of America	Utah
Rockville, Maryland	United States of America	Maryland
Milton, MA	United States of America	Massachusetts
Savignano sul Rubicone	Italy	Emilia-Romagna
Hatherleigh, Devon, UK	United Kingdom	England

Table A19—Random sample of 100, confidence=5 (96% accuracy)

Location string	Geocoded country	Geocoded state
Los Alamos, NM	United States of America	New Mexico
Saint-Quentin, France	France	Hauts-de-France
Mariehamn, Åland	Finland	—
Cambridge MA	United States of America	Massachusetts
Shibuya-ku, Tokyo	Japan	—
Victoria, British Columbia, Canada	Canada	British Columbia
Charlottesville, VA	United States of America	Virginia
Not San Francisco	**France**	**Nouvelle-Aquitaine**
Aylesbury, UK	United Kingdom of Great Britain and Northern Ireland	England
Jerseyville, IL.	United States of America	Illinois
Commerce	**United States of America**	**California**
Zaandam	Netherlands	Noord-Holland
Forest Grove Oregon	United States of America	Oregon
Port Washington, WI	United States of America	Wisconsin
Uhldingen, Germany	Germany	Baden-Württemberg
The Netherlands, Delft.	Netherlands	Zuid-Holland
Silla	Spain	Comunitat Valenciana
Nelsonville, OH, USA	United States of America	Ohio
Brookline, MA, USA	United States of America	Massachusetts
Beverly Hills, California	United States of America	California
Granollers, Barcelona	Spain	Catalunya
Feurs	France	Auvergne-Rhône-Alpes
Brighton, England	United Kingdom of Great Britain and Northern Ireland	England
Fuengirola, Málaga, Spain	Spain	Andalucía
Kockengen, The Netherlands	Netherlands	Utrecht
Los Altos Hills, CA	United States of America	California
Ferndale, WA, USA	United States of America	Washington
Grenoble, Isère, France	France	Auvergne-Rhône-Alpes
Davenport, FL	United States of America	Florida
New Westminster, BC, Canada	Canada	British Columbia
Manchester,CT	United States of America	Connecticut
Mataró, Catalonia	Spain	Catalunya
Kailua, Hawaii	United States of America	Hawaii
Victoria, Canada	Canada	British Columbia
Aberdeen, MD	United States of America	Maryland
Sant Fruitós de Bages (Barcelona)	Spain	Catalunya
Louisville, CO	United States of America	Colorado
Williamsburg, VA	United States of America	Virginia
Margate	United Kingdom of Great Britain and Northern Ireland	England
Amagansett, NY	United States of America	New York
France - Arzon	France	Bretagne
Grenoble France	France	Auvergne-Rhône-Alpes
Merelbeke, Belgium	Belgium	Vlaanderen
Schoonebeek	Netherlands	Drenthe
Clemson, SC, USA	United States of America	South Carolina
Marcq-en-Barœul, France	France	Hauts-de-France
Flehingen, Germany	Germany	Baden-Württemberg
San Carlos, California, USA	United States of America	California
Teltow, Germany	Germany	Brandenburg
Savenay, France	France	Pays de la Loire
Taos, NM	United States of America	New Mexico
Clemson, South Carolina	United States of America	South Carolina
France, Grenoble	France	Auvergne-Rhône-Alpes
Veenendaal, The Netherlands	Netherlands	Utrecht
Basel - Switzerland	Switzerland	Basel-Stadt
Moab, Utah	United States of America	Utah
Lone Tree, CO	United States of America	Colorado
Tourcoing, France	France	Hauts-de-France
Grenoble, FRANCE	France	Auvergne-Rhône-Alpes
Scotts Valley, CA	United States of America	California
Victoria BC	Canada	British Columbia
Grenoble, France	France	Auvergne-Rhône-Alpes
Grenoble - FR	France	Auvergne-Rhône-Alpes
Grenoble	France	Auvergne-Rhône-Alpes
Cambridge, USA	United States of America	Massachusetts
Mt. Pleasant, MI	United States of America	Michigan
L'ile d'Elle	France	Pays de la Loire
New Westminster	Canada	British Columbia
Maarssen, The Netherlands	Netherlands	Utrecht

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Table A19 – Continued from previous page

Location string	Geocoded country	Geocoded state
San Carlos, CA	United States of America	California
Covington, WA	United States of America	Washington
Schiedam, The Netherlands	Netherlands	Zuid-Holland
Medford, NY	United States of America	New York
San Lorenzo- Santa Fe- Argentina	Argentina	Santa Fe
Malabar, FL	United States of America	Florida
Geneve, Switzerland	Switzerland	Genève
Salisbury, Wiltshire	United Kingdom of Great Britain and Northern Ireland	England
Saint Priest sous Aixe (Limousin - France)	France	Nouvelle-Aquitaine
Netherlands - Heiloo	Netherlands	Noord-Holland
Delft, The Netherlands	Netherlands	Zuid-Holland
Borlänge	Sweden	Dalarnas län
Done	**Indonesia**	**Nusa Tenggara Timur**
Bilthoven	Netherlands	Utrecht
San Bruno, CA	United States of America	California
Caen, France	France	Normandie
Kailua, HI US	United States of America	Hawaii
Woodstock, NY	United States of America	New York
Albany, California	United States of America	California
Innopolis, Russia.	Russian Federation	Татарстан
eu	**France**	**Normandie**
Alliance, Ohio	United States of America	Ohio
Merelbeke, Belgium.	Belgium	Vlaanderen
Modiin, Israel	Israel	מחוז המרכז
Makati, Philippines	Philippines	—
Altenholz, Germany	Germany	Schleswig-Holstein
Santiago, Chile	Chile	Región Metropolitana de Santiago
Bilthoven, Utrecht, the Netherlands	Netherlands	Utrecht
Mataró	Spain	Catalunya
Valkenburg, The Netherlands	Netherlands	Limburg
Cambridge, Massachusetts	United States of America	Massachusetts

Table A20—Random sample of 100, confidence=6 (92% accuracy)

Location string	Geocoded country	Geocoded state
Chernogolovka, Russia	Russian Federation	Московская область
valentine	France	Occitanie
Barr, Ayrshire, Scotland	United Kingdom	Scotland
Roseville, CA	**Canada**	**Ontario**
Margretetorp	Sweden	Skåne län
UK / Canada	United Kingdom	England
Flax Bourton, Bristol, UK	United Kingdom	England
Talence, France	France	Nouvelle-Aquitaine
Melville, WA, Australia	Australia	Western Australia
Phoenixville, PA	United States of America	Pennsylvania
Sandpoint, Idaho	United States of America	Idaho
Vienna, VA	United States of America	Virginia
Danville, PA	United States of America	Pennsylvania
Kula, Hawaii	United States of America	Hawaii
Hever (Belgium)	Belgium	Vlaanderen
Cricklewood, London, UK	United Kingdom	England
New Lebanon, NY	United States of America	New York
St. John's, NL	**Netherlands**	**Caribisch Nederland**
Casoria (Na)	Italy	Campania
No simple highway	**France**	**Pays de la Loire**
Heemstede, Netherlands	Netherlands	Noord-Holland
BHM	**United States of America**	**Alabama**
Miami Lakes, FL	United States of America	Florida
nyon, switzerland	Switzerland	Vaud
Blanc Mesnil, France	France	Île-de-France
CA :: NY :: [...China]	United States of America	New York
Houston, TX & Germany	United States of America	Texas
chuo-ku, Japan	Japan	—
Boston / New York	United States of America	New York
Lilburn, GA	United States of America	Georgia
Wartenberg, Germany	Germany	—
Sevenoaks Weald, Kent	United Kingdom	England
Mohali, India	India	Punjab
Vélizy, France	France	Île-de-France
Greenbelt MD	United States of America	Maryland
Lansdale, PA	United States of America	Pennsylvania
University Park, Pennsylvania	United States of America	Pennsylvania
Felton, CA	**Canada**	**Ontario**
Smolenice	Slovakia	Trnavský kraj
Snohomish WA	United States of America	Washington
San Pedro, CA	United States of America	California
Irvington, NY	United States of America	New York
.Netland	Norway	—
Louvain-La-Neuve Valley	Belgium	Wallonie
Tassin-la-Demi-Lune - France	France	Auvergne-Rhône-Alpes
RDU	United States of America	North Carolina
Pully - Switzerland	Switzerland	Vaud
Ithaca, NY and New York, NY	United States of America	New York
the yay	**Lao People's Democratic Republic**	—
Chengdu, Sichuan Province, China.	China	四川省
Muri bei Bern, BE, Switzerland	Switzerland	Bern/Berne
Fairfax Va	United States of America	Virginia
Embrach, Switzerland	Switzerland	Zürich
Pontoise (France)	France	Île-de-France
HERE	**Bosnia and Herzegovina**	**Federacija Bosne i Hercegovine**
Hebron, KY	United States of America	Kentucky
San Diego, U.S.	Venezuela (Bolivarian Republic of)	Táchira
Lewes, UK	United Kingdom	England
Louvain-la-Neuve	Belgium	Wallonie
Lopătari, Romania	Romania	—
Wals, Salzburg, Austria	Austria	Salzburg
Wasserbillig, Luxembourg	Luxembourg	—
Argonne, IL, US	United States of America	Wisconsin
Texas Tech University	United States of America	Texas
The University of Iowa	United States of America	Iowa
North Carolina, Texas	United States of America	North Carolina

Continued on next page

Table A20 – Continued from previous page

Location string	Geocoded country	Geocoded state
Oak Cliff, TX	United States of America	Texas
Smithfield, Utah, USA	United States of America	Utah
Yrisarri, NM	United States of America	New Mexico
Cádiz	Spain	Andalucía
Graton, CA	United States of America	California
State College, PA	United States of America	Pennsylvania
Asnieres-sur-Seine, France	France	Île-de-France
30% of the web	**Ethiopia**	**Oromia**
Guangdong Province, China	China	广西壮族自治区
Orsay	France	Île-de-France
Winfield, IL	United States of America	Illinois
Saratoga Springs, Utah	United States of America	Utah
College Place, WA, USA	United States of America	Washington
Brunswick, MD	United States of America	Maryland
Iver Heath	United Kingdom	England
Fairfax Station, VA	United States of America	Virginia
Tuxedo Park, NY	United States of America	New York
Bampton, Oxfordshire, UK	United Kingdom	England
Reach	United Kingdom	England
四川成都	China	四川省
Europe, Potsdam	Germany	Schleswig-Holstein
Denderleeuw, Belgium	Belgium	Vlaanderen
Racour	Belgium	Wallonie
Yangling, China	China	宁夏回族自治区
Morristown, NJ	United States of America	New Jersey
Hanover, Maryland	United States of America	Maryland
Creil, France	France	Hauts-de-France
Hawthorne, NJ	United States of America	New Jersey
Gümligen	Switzerland	Bern/Berne
Gorssel, Gelderland, The Netherlands	Netherlands	Gelderland
Rocky River, Ohio	United States of America	Ohio
Kreuzberg, Berlin, Germany	Germany	—
Nyon, Switzerland	Switzerland	Vaud
Berlin, NY	United States of America	New York

Table A21—Random sample of 100, confidence=7 (82% accuracy)

Location string	Geocoded country	Geocoded state
Akihabara, Tokyo	Japan	—
shaibu	China	广东省
Kremlin-Bicêtre, France	France	Île-de-France
Aichi, Japan	Japan	—
19 Countries	**Saudi Arabia**	—
National University of Singapore	Singapore	—
Falls Church VA	United States of America	Virginia
Oakdale, CA	Canada	Ontario
Israel, Afula	Israel	מחוז הצפון
Caltech, Pasadena, CA	United States of America	California
Rokko, Kobe, JAPAN	Japan	—
Bresso, Milano - Italy	Italy	Lombardia
Skipton, North Yorkshire	United Kingdom	England
Asbury Park, NJ	United States of America	New Jersey
Jersey Shore	United States of America	Pennsylvania
Wilkinsburg, PA	United States of America	Pennsylvania
Florence, MA USA	United States of America	Massachusetts
Villetaneuse, France	France	Île-de-France
Appalachian State University	United States of America	North Carolina
仙桃.湖北	**Japan**	—
The milky way	**Seychelles**	—
tero	Norway	—
Sibuya, Tokyo	Japan	—
Galt's Gulch	**United States of America**	**Utah**
University of Canterbury, Christchurch, New Zealand	New Zealand	Canterbury
SZ China	China	广东省
Mvd	**Uruguay**	**Canelones**
West Grove, PA, USA	United States of America	Pennsylvania
Bellport, NY	United States of America	New York
Shinjuku, Tokyo	Japan	—
Milky Way	**Seychelles**	—
Otava, Mikkeli, Finland	Finland	—
Dunston, Staffordshire	United Kingdom	England
Windber, PA, USA	United States of America	Pennsylvania
Oberentfelden / Switzerland	Switzerland	Aargau
void	**France**	**Grand Est**
Viroflay France	France	Île-de-France
Notre Dame, IN	United States of America	Indiana
Laporte, Minnesota, USA	United States of America	Minnesota
UCSB	United States of America	California
Towaco, NJ	United States of America	New Jersey
Chicagoland, IL	United States of America	Illinois
Greenfield, IA	United States of America	Iowa
Peking University, Beijing, China	China	北京市
University of Virginia	United States of America	Virginia
University of Waterloo, Waterloo ON, Canada	Canada	Ontario
Broek op Langedijk, The Netherlands	Netherlands	Noord-Holland
Larkspur, CA	**Canada**	**Alberta**
Rhineland	United States of America	Missouri
Northbrook, IL	United States of America	Ohio
Interstellar	**United States of America**	**California**
Ebisu, Tokyo, Japan	Japan	—
Deuil la barre, France	France	Île-de-France
Philadelphia, NY	United States of America	New York
Taplow, UK	United Kingdom	England
North Germany	Germany	Bayern
Harvard University, Cambridge, MA, USA	United States of America	Massachusetts
milky way	**Seychelles**	—
Sliema, Malta	Malta	Ċentrali
Ås, Krokom, Sweden	Sweden	Jämtlands län
CWRU, Cleveland, OH	United States of America	Ohio
New Paltz, NY	United States of America	New York
North Newton, KS	United States of America	Kansas
Arakawa, Tokyo, Japan	Japan	—
Pleasant Hill, CA	Canada	—
General Fernandez Oro, Rio Negro, Argentina	Argentina	Río Negro
Woodbridge VA	Australia	Western Australia
Kennett Square, PA, USA	United States of America	Pennsylvania
Burnie, Tasmania, Australia	Australia	Tasmania

Continued on next page

Table A21 – Continued from previous page

Location string	Geocoded country	Geocoded state
Washington University in St Louis	United States of America	Missouri
Berkley, CA	United States of America	Iowa
Null island	**Germany**	**Thüringen**
PID 0	**France**	**Centre-Val de Loire**
52°51 N 13°373 E	**Poland**	**województwo kujawsko-pomorskie**
Åre	Sweden	Jämtlands län
Genval, Belgium	Belgium	Wallonie
CMU, Pittsburgh, PA	United States of America	Pennsylvania
Kensington, MD	United States of America	Maryland
Økern, Oslo	Norway	—
Saint Ouen	France	Hauts-de-France
moravia	United States of America	Iowa
Earth.	**United States of America**	**Texas**
University of California, Irvine	United States of America	California
University of Canterbury, New Zealand	New Zealand	Canterbury
Steinhausen, Switzerland	Switzerland	Zug
Amoy Fujian China	China	福建省
SJO, Costa Rica	Costa Rica	Provincia Alajuela
UTC -5	**United States of America**	**California**
Capellades, Catalunya	Spain	Catalunya
Roxborough, CO	**United States of America**	**Pennsylvania**
Bø Telemark, Norway	Norway	—
Florida State University	United States of America	Florida
Mountainview, CA	**Canada**	**Alberta**
Bliżyn, Poland	Poland	województwo świętokrzyskie
Wuhan University, Hubei, China	China	湖北省
Black Rock City	United States of America	Nevada
Nay Beijing	China	北京市
Union City, CA 94587	United States of America	California
All around you	**China**	**浙江省**
Brighton, CO	United States of America	Colorado

Table A22—Random sample of 100, confidence=8 (64% accuracy)

Location string	Geocoded country	Geocoded state
Downey, CA	**Canada**	**British Columbia**
University of Minnesota Morris	United States of America	Minnesota
home	**Germany**	**Nordrhein-Westfalen**
Nomad	**United States of America**	**New York**
1108 Western Avenue, Brattleboro, VT 05301	United States of America	Vermont
Near the edge of the world...	**Australia**	**Western Australia**
127.88.88.88	**Philippines**	—
Eastern Europe	**Poland**	**województwo śląskie**
Development Heaven	**United States of America**	**Washington**
Moon of Endor	**Australia**	**Western Australia**
Pacific University, Forest Grove OR	United States of America	Oregon
$HOME, Germany	Germany	Nordrhein-Westfalen
The multiverse	**United Kingdom**	**Scotland**
Lynbrook High School	United States of America	California
/home	**Germany**	**Nordrhein-Westfalen**
Potsdam (Berlin)	Germany	Schleswig-Holstein
Slavyansk, Ukraine	Ukraine	Донецька область
Southern Maine	United States of America	Maine
Politechnika Wrocławska	Poland	województwo dolnośląskie
École de technologie supérieure	Canada	Québec
Everywhere :)	**Romania**	—
Zürich & Winterthur, Switzerland	Switzerland	Zürich
百度科技园 2 号楼	China	北京市
HCMC, VN	**United States of America**	**Minnesota**
Tricity Poland	Poland	województwo pomorskie
The Dark Side of the Moon	**United States of America**	**West Virginia**
Hararit, Israel	Israel	מחוז הצפון
Western Massachusetts, USA	United States of America	Massachusetts
Mountain View High School, Vancouver, WA	United States of America	Washington
University College London	United Kingdom	England
Deakin University	Australia	Victoria
50.758977, 6.082807	Germany	Nordrhein-Westfalen
Paris & Saclay	France	Île-de-France
Москва, НИЯУ МИФИ	Russian Federation	Москва
The Middle of Nowhere	**Canada**	**British Columbia**
Sol III	**Chile**	**Región de Atacama**
Mars; 火星	**Russian Federation**	**Московская область**
Terra / Earth	**Italy**	—
Bangalore/Pune	India	Karnataka
198.41.0.4	**Yemen**	—
B.C. Canada	Canada	Ontario
Paris Area	Venezuela (Bolivarian Republic of)	Miranda
the Universe	**Denmark**	**Region Syddanmark**
Canada/Israel	**Israel**	**מחוז המרכז**
St. Petersburg state university, Russia	Russian Federation	Санкт-Петербург
Northern Idaho	United States of America	Michigan
UNR	**Argentina**	**Santa Fe**
Majaka 26-211, 11411 Tallinn	Estonia	—
Tatooine	**United States of America**	**Vermont**
University of Auckland	New Zealand	—
-95.3m	**France**	**Hauts-de-France**
Bengaluru, Tamil Nadu	India	Tamil Nadu
Imperial College London, United Kingdom	United Kingdom	England
University of Science and Technology of China	China	安徽省
University of Auckland, New Zealand	New Zealand	—
54.706901, 20.4981673	Russian Federation	Калининградская область
University of Auckland, Auckland, New Zealand	New Zealand	—
Nanterre (Paris, France)	France	Île-de-France
West Visayas State University La Paz, Iloilo City, Philippines	Philippines	—
Greater Philadelphia Area, PA USA	United States of America	Pennsylvania
Mérida, Yuc., Mex.	Mexico	Yucatán
Greater Philadelphia Area, PA	United States of America	Pennsylvania
Home	**Germany**	**Nordrhein-Westfalen**
Universidad de Jaén	Spain	Andalucía
Lakewood, Colorado	United States of America	Colorado
Hubei.Wuhan.China	China	湖北省
Lakewood, Colorado, USA	United States of America	Colorado
Chinese Taipei	Taiwan, Province of China	臺北市
Somewhere, Utah	United States of America	Utah

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Table A22 – Continued from previous page

Location string	Geocoded country	Geocoded state
Everywhere.	**Romania**	—
The Upside-Down	**Canada**	**Saskatchewan**
In the middle of nowhere	**Canada**	**British Columbia**
UCL	United Kingdom	England
Monument, Colorado	United States of America	Colorado
The clouds	**Thailand**	
Half Moon Bay, CA	Canada	Alberta
Queen Mary University of London	United Kingdom	England
All over the US & Canada	**Spain**	**Andalucía**
philly	United States of America	Pennsylvania
SF, Paris	**Argentina**	**Santa Fe**
Vadodara (Baroda), India	India	Gujarat
1200 Park Avenue Emeryville CA 94608	United States of America	California
Westeros	**Germany**	**Brandenburg**
Hitotsubashi, Chiyoda-ku, Tokyo 101-8430, Japan	Japan	—
Germany, Lusatia	Germany	Sachsen
Dagobah	**United States of America**	**Oregon**
Now-here	**United States of America**	**Pennsylvania**
Rishon LeTzion, Israel	Israel	מחוז המרכז
Brno, Moravia, Czech Republic	Czechia	Moravskoslezsko
Greater Philadelphia Area, USA	United States of America	Pennsylvania
Vienna / Rome	**France**	**Nouvelle-Aquitaine**
Imperial College London	United Kingdom	England
Sandhurst, Berks.	United States of America	Pennsylvania
Silesia/Poland	Poland	województwo dolnośląskie
San Franscico	Brazil	Bahia
HCMC	**United States of America**	**Minnesota**
ucsf	United States of America	California
Malaysia, Earth	Malaysia	—
Everywhere!	**Romania**	—
Chihuahua, Chih. México	Mexico	Chihuahua

Table A23—Random sample of 100, confidence=9 (72% accuracy)

Location string	Geocoded country	Geocoded state
us-west-1	**United States of America**	**Illinois**
Brussels, EU	Belgium	Région de Bruxelles-Capitale - Brussels Hoofdstedelijk Gewest
Shinjyuku, Tokyo, Japan	Japan	—
Moscow/SPb, RU	Russian Federation	Санкт-Петербург
UTT, Troyes, France	France	Grand Est
Kondavil , Jaffna, Sri Lanka	Sri Lanka	—
Sunny San Diego	United States of America	Texas
Berkeley & SF	United States of America	California
Málaga (Spain)	**Philippines**	**Laguna**
Malibu, CA	**Canada**	**Québec**
China/Asia	**Venezuela (Bolivarian Republic of)**	**Bolívar**
ПМР Тирасполь (PMR Tiraspol)	Moldova, Republic of	Нистрения / Приднестровье / Придністров'я
on the road I am	**Australia**	—
IFCE - Campus Maracanau	Brazil	Ceará
New Wesminster, BC	United States of America	Missouri
The High Seas	**United States of America**	**Texas**
19700 Helix Drive, Ashburn, VA 20147	United States of America	Virginia
Madrid | Jaén, Spain	Spain	Andalucía
深圳 ShenZhen	China	广东省
Psalm 91	**Philippines**	—
Erie, CO	United States of America	Colorado
Austin and Houston, Texas	United States of America	Texas
TBD	**Falkland Islands (Malvinas)**	—
Victoria Junior College	Singapore	—
Jackson Wy	United Kingdom	England
Wellcome Sanger Institute	United Kingdom	England
大都会	**China**	**江西省**
Santa Monica, CA	Canada	Québec
Vikingskipet, Hamar, Norway	Norway	—
2788 San Tomas Expressway, Santa Clara, CA, 95051	United States of America	California
Rambouillet / Versailles / Paris / Tokyo	France	Île-de-France
Bay Area | Houston TX	United States of America	Texas
Home, United Kingdom	United Kingdom	Scotland
Babylon, Long Island	**Iraq**	
Herts, UK	United Kingdom	England
github.com	Brazil	Rio de Janeiro
Shanghai, Asia	China	上海市
Barcelona (UPC)	Spain	Catalunya
R.Korea suwon	Korea, Republic of	—
Córdoba - Spain	**Philippines**	**Laguna**
2, Toegye-ro 36-gil, Jung-gu, Seoul, Republic of Korea	Korea, Republic of	—
UC Santa Cruz	**Argentina**	**Chaco**
jiangsu changzhou china	China	江苏省
Paris/Prague	France	Île-de-France
San Mateo, CA and Buenos Aires, Argentina	**Argentina**	**Buenos Aires**
Auburn, Alabama	United States of America	Alabama
Abuja/Lagos, Nigeria	Nigeria	Lagos
All around the world.	**Canada**	**British Columbia**
The (Middle) Earth	**United States of America**	**California**
Goiânia - Porangatu - GO - Brazil	Brazil	Goiás
Chicago area	**Philippines**	**Rizal**
Naarm	India	Telangana
Belem, Amazonia, Brazil	Brazil	Goiás
Chicago Area	**Philippines**	**Rizal**
Russian, Saint-Petersburg	Russian Federation	Санкт-Петербург
Remote Ok	United States of America	Oklahoma
The Wandering Sea	**United States of America**	**Florida**
University of Luxembourg	Luxembourg	—
McEnery Convention Center	United States of America	California
San Francisco/Munich	**Chile**	**Región de Arica y Parinacota**
128 avenue du Maréchal De Lattre de Tassigny, 87000 Limoges, France	France	Nouvelle-Aquitaine
Middle Earth	**United States of America**	**California**
Metro Detroit, Michigan	United States of America	Michigan
41°52'57.0"N 87°37'18.5"W	United States of America	Illinois
Washington D.C Metro	United States of America	District of Columbia
Vestlandet, Norway	Norway	—

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Table A23 – Continued from previous page

Location string	Geocoded country	Geocoded state
Chicago & SF	**United States of America**	**California**
St. Thomas, VI	**Philippines**	—
Europe, Germany	Germany	Schleswig-Holstein
TEDA, Tianjin, China	China	天津市
Paris, Nice	France	Provence-Alpes-Côte d'Azur
IIIT Bangalore	India	Karnataka
Metro-Detroit/Ann Arbor	United States of America	Michigan
Auburn, AL USA	United States of America	Alabama
No.6 Kexueyuan South Road Zhongguancun, Haidian District Beijing, China	China	北京市
Germany, Europe	Germany	Schleswig-Holstein
rhode island/florida	**United States of America**	**Florida**
Glasgow / New Eden	United Kingdom	Scotland
Metro Washington D.C.	United States of America	District of Columbia
China.CS	China	福建省
DMC	**United States of America**	**Pennsylvania**
CS, China	China	福建省
Chinese Beijing	China	北京市
Up in the air	**Malaysia**	**Pulau Pinang**
The British Museum	United Kingdom	England
Paris - La Défense / France	France	Île-de-France
Ottawa & Waterloo	Canada	Ontario
Ottawa, ON and Waterloo, ON	Canada	Ontario
1 Cyclotron Rd, Berkeley CA 94720	United States of America	California
Central Coast NSW, Australia	Australia	—
Arvada, Colorado, USA	United States of America	Colorado
Sydney, Bronte Beach	Australia	—
University of California, Davis	United States of America	California
Dubai/Novi Sad	**Ukraine**	**Львівська область**
Russia, KHMAO	Russian Federation	Ханты-Мансийский автономный округ —Югра
East Bay, California, USA	United States of America	California
france, le thor vaucluse	France	Provence-Alpes-Côte d'Azur
Moscow Region	**Philippines**	—
Auburn Alabama	United States of America	Alabama
León Guanajuato, México	Mexico	San Luis Potosí