0.264 (rows F-B, F-C, G-B, G-C from Appendix Table C1, columns 2-4).[16] In other words, there is scant indication of medium or long-term disemployment effects in any of these models.

One concern with parametric trend controls is that they may incorrectly reflect delayed effects of treatment (Wolfers 2006, Meer and West 2015). However, including 12 quarters of leads and lags in our dynamic specifications means that the trends are identified using only variation outside of the 25 quarter window around minimum wage increases, and are unlikely to reflect lagged or anticipation effects

When using the 4 quarters prior to treatment as baseline, the long-run estimates in Table 3 for models with some controls for time-varying heterogeneity range between -0.049 (column 2) to 0.162 (column 4). These estimates compare to an estimate of -0.106 from the two-way fixed effects model (column 1). Two limitations are important when interpreting these longer term effects. First, the variation to estimate these effects is more limited, making them less precise. Second, different from short and medium term effects, the 4+ year effects affect the estimation of state-specific trends. With those caveats in mind, we find little indication of more negative impacts in the longer run.

First-difference versus deviations-from-means estimators

When using state-aggregated data, first-differencing is an alternative to taking deviations-from-means for purging the state fixed effects. While each approach has its advantages, the first-difference estimator is less prone to bias if the state effects are not "fixed" and are time-varying instead.

[16]This conclusion is qualitatively similar in the NSW sample (Online Appendix C, Table C1, columns 2, 3 and 4) where the equivalent range is (-0.033, 0.395).

Table 2. Model selection: Minimum wage elasticities for teen employment, state-quarter aggregated CPS data 1979-2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full sample (1979-2014)								
Common time FE	-0.168**	0.025	0.004	-0.051	-0.084	-0.069		
	(0.066)	(0.081)	(0.075)	(0.078)	(0.081)	(0.085)		
N	7,344	7,344	7,344	7,344	7,344	7,344		
Division-period FE	-0.037	0.059	0.058	0.038	0.006	0.005		
	(0.088)	(0.057)	(0.056)	(0.049)	(0.049)	(0.055)		
N	7,344	7,344	7,344	7,344	7,344	7,344		
LASSO-selected division-period FE							0.015	-0.009
							(0.082)	(0.083)
N							7,344	7,344
Panel B: Post-1990 sample (1990-2014)								
Common time FE	-0.100	0.009	-0.053	-0.141**	-0.168**	-0.199***		
	(0.065)	(0.078)	(0.065)	(0.067)	(0.068)	(0.063)		
N	5,100	5,100	5,100	5,100	5,100	5,100		
Division-period FE	-0.021	0.076	0.051	-0.006	-0.015	-0.053		
	(0.093)	(0.063)	(0.061)	(0.057)	(0.070)	(0.062)		
N	5,100	5,100	5,100	5,100	5,100	5,100		
LASSO-selected division-period FE							-0.002	-0.024
							(0.072)	(0.069)
N							5,100	5,100
State-specific trend type:								
Linear		Y	Y	Y	Y	Y		
Quadratic			Y	Y	Y	Y		
Cubic				Y	Y	Y		
Quartic					Y	Y		
Quintic						Y		
LASSO-selected trends (linear only)							Y	
LASSO-selected trends (up to quintic)								Y

Notes: The table reports minimum wage elasticities for teen employment, using state-quarter aggregated CPS basic monthly data from 1979-2014. The dependent variable is the log of the state-quarter sample-weighted mean of teen employment. The reported estimates are coefficients for log quarterly minimum wage. All regressions include controls for the overall quarterly state unemployment rate, the quarterly teen share of the working age population, and state-quarter means for demographic controls used in Table 1 and state fixed effects. Specifications include either common period effects, or Census division-period effects, and up to fifth order polynomial trends by state. Columns 7-8 report double-selection post-LASSO estimates where controls (besides state and period effects) are selected using LASSO regressions predicting teen employment and minimum wage: these include demographic controls, division-period effects, and state-specific trends (linear in specification 7; up to quintic in specification 8). Regressions are weighted by teen population. Robust standard errors in parentheses are clustered by state; significance levels are *** 1%, ** 5%, * 10%.

employment estimates are substantially smaller. None of the 3 or 4+ year out effects exceeds -0.1 in magnitude, regardless of baselines (one, two or three years before) or specifications. As expected, the precision of some of the estimates is lower in the smaller sample; but the overall conclusion is qualitatively similar when we use the 199-2011 NSW sample, as it is for the full 1979-2014 sample used in this paper.

Sina Nader, head of encryption at Robinhood, a San Francisco-based stock and encryption trading platform, has left, the sources said. Robinhood is currently hiring an encryption operations manager. In the middle of this month, Robinhood raised another $320 million at a valuation of $8.6 billion, while round F raised $600 million. Note: Robinhood originally launched its cryptocurrencies trading service in February 2018. Sina Nader joins Robinhood as head of the company's encryption business at the end of 2019.
The company said Robinhood Crypto aims to expand our user base to expand existing revenue streams such as Robinhood.
Technologies, Robinhood, Pinterest, Postmates and WeWork.
Robinhood - Integrated Financial Products Import Robinhood is a U.S.-based financial services company based in Menlo Park, California. The company offers a Robinhood smartphone mobile app that allows individuals to invest in publicly traded companies and exchange-traded funds listed on U.S. stock exchanges without paying commissions. Robinhood is a feature of Robinhood because of its huge volume of transactions and the fact that it delivers orders to professional marketmakers such as Citadel, who pay commissions.
Sina Nader, head of encryption at Robinhood, a San Francisco-based stock and encryption trading platform, has left her job, The Block reported. Robinhood is currently hiring an encryption operations manager. In the middle of this month, Robinhood raised another $320 million at a valuation of $8.6 billion, while round F raised $600 million, chain news reported earlier. Robinhood originally launched its cryptocurrencies trading service in February 2018. Sina Nader joined Robinhood as head of the company's encryption business at the end of 2019.
Sina Nader, head of encryption at Robinhood, a San Francisco-based stock and encryption trading platform, has left, sources said, according to The Block. Robinhood is currently hiring an encryption operations manager. In the middle of this month, Robinhood raised another $320 million at a valuation of $8.6 billion, while round F raised $600 million, chain news reported earlier. Robinhood originally launched its cryptocurrencies trading service in February 2018. Sina Nader joined Robinhood as head of the company's encryption business at the end of 2019.
Foreign media recently reported that the stock trading app and cryptocurrencies exchange Robinhood acquired media company MarketSnacks and renamed its brand Robinhood.
Square is another trading app after Robinhood that announced the launch of a Bitcoin trading service. On Thursday, Robinhood announced that it would be in February.
Dogecoin founder Jackson Palmer commented on Twitter.
Baiju Bhatt, chief executive of Robinhood, a digital currency trading platform, said Robinhood was preparing to go public and was now valued at $5.6bn. (TechCrunch)
In response to 51 per cent of attack concerns, Dogecoin merged its mining with Litecoin in 2014 to enable both assets to

be mined at the same time. Notably, the joint mining of Litecoin and Dogecoin affected Lee's new pool donation concept.

Robinhood, the cryptocurrencies trading app, announced late Wednesday that it had officially launched Robinhood Securities, a clearing system, according to SludgeFeed. In an email to Robinhood users, the company said Robinhood Securities was operational and would handle trading activities on the platform.

Bhatt said he hoped Robinhood would play an important role in cryptocurrencies. But he declined to say how many of Robinhood's more than 4 million users were also using Robinhood's cryptocurrencies trading app, Robinhood Crypto, or when Robinhood would trade in cryptocurrencies other than existing bitcoins and Ethers.

Tesla and SpaceX CEO Elon Musk tweeted a Meme-based tweet to promote Dogecoin (DOGE) again. This is the second time that Musk has implicitly supported Dogecoin after Musk posted his "favorite coin" on Twitter in the summer of 2019. (Bitcoinist)

Dog Coin (DOGE) icon Dogecoin was born out of a tweet, a joke. In 2013, dog dog image was so popular that Palmer, a flat-shooting and marketing expert at Adobe Sydney and a cryptocurrencies researcher, tweeted semi-jokingly, "Invest in Dogecoin, this is the next big opportunity." After the tweet, there was a lot of support, and Palmer was very effective in buying the domain name dogecoin a week later. Meanwhile, in another part of the globe, Markus, a programmer in Brandt, has been trying to create a cryptocurrencies. Markus came across the site and contacted Palmer for help. Before Palmer replied, he set out to transform the source code of Bitcoin, adding elements to Doge Mene. Palmer quickly replied to Markus, and the two clapped together. Eventually, dogecoin was born more than a week after the half-joking tweet. Dogecoin was born and developed so smoothly that it can even be described as hot. For Dogecoin itself, there are two main reasons for the boom: First, Dogecoin brings its own social attributes. On social networking sites such as Reddit, Dogecoin's content was very popular before it was born. When Dogecoin was born, it was greatly assisted by sites like Reddit. Dogecoin has far more attention on social networking sites than Bitcoin, Litecoin and other shanzhai coins. Second, Dogecoin's tip and charitable culture are recognized. Dogecoin advocates a tip culture, which has been used by many people for activities such as rewards in just one week, showing the level of recognition of its tip culture. Dogecoin is also more recognized in terms of philanthropy, and its charitable support is already extensive.

The Dogecoin community is responsible for the creation of the Dogecoin Foundation, a non-profit organization that promotes the use of Dogecoin through goodwill and charitable activities. These activities included a $30,000 DOGE donation to the Jamaican bobsleigh team at the 2014 Winter Olympics and an additional $30,000 to Kenya's Clean Water Initiative.

Continuing with the common time effect models in the first row of Table 1, panel B, when we include state-specific trends of higher order, the coefficients are always smaller than -0.09 in magnitude and none is statistically significant. Four out of five estimates are less than -0.07 in magnitude. These results refute the claim in NSW that inclusion of higher order (third or greater) state-specific trends restores the finding of a sizable negative effect. Estimation of cubic, quartic or quintic trends by state places greater demand upon the data, especially when the panel is short. By using a substantially longer panel, we estimate these trends more reliably. The estimates from including 3rd and 5th order polynomials, -0.061 and -0.088, respectively are virtually identical to the estimate with just a linear trend (-0.062). The estimate from the 2nd order trend is slightly smaller in magnitude (-0.040) while the estimate from the 4th order trend is slightly larger in magnitude (-0.088). However, in all cases, the estimates are under -0.09 in magnitude and never statistically significant. Overall, these results suggest that including higher order trends are unlikely to change the conclusions reached in ADR.

The bottom section of panel B of Table 1 additionally includes division-period effects, isolating the identifying variation to within the nine census divisions. Including division-period effects typically produces estimates that are even less negative. For example, without any state trends (column 1) the estimate falls from -0.214 to -0.124 in magnitude, and is not statistically significant. However, inclusion of state trends renders the estimates close to zero and not statistically significant, with point estimates ranging between -0.037 and 0.011. We note that the lack of statistical significance in the more saturated models is not due to lack of precision, but rather due to the small size of the coefficients.

---

state trends are included. Moreover, Online Appendix B shows that excluding downturns—either using the official NBER definition or a much more expansive one—does not produce evidence of substantial disemployment effects in models with state trends.

these results imply labor demand elasticities generally smaller than -0.3 in magnitude. Moreover, all of these estimators, including NSW's preferred matching estimator, suggest employment effects that are usually substantially smaller than the two-way fixed-effects model. (An exception is Addison et al.'s 1990-2012 sample; as reported in our Online Appendix Table E1, they find a zero effect even for the two-way fixed effects model.) While there may be disagreement about the merits of specific estimators, these results comprise a highly robust set of findings. They confirm: (1) at most a modest impact of minimum wages to date on restaurant employment, and (2) the violation of the parallel trends assumption in the two-way fixed-effects model, and likely bias toward finding evidence of job loss.

There are some remaining disagreements on the details of the restaurant findings. For instance, NSW (2014a, 2014b) criticize a falsification test we performed in DLR to demonstrate the unreliability of the two-way fixed effects estimates; we respond to these criticisms in Online Appendix F. The key takeaway nevertheless remains: the research literature seems to be reaching an agreement on the medium-run effects of minimum wages on restaurant employment.

Conclusion

Much of the minimum wage research on employment effects has focused on teens and on restaurant workers because these two groups are especially affected by minimum wage policies. A wide variety of recent restaurant studies using different datasets, time periods and estimators arrive at similar findings. In these studies, the preferred elasticities of employment with respect to minimum wages lie within a fairly narrow range of -0.063 and 0.039, suggesting at most a

---

which they interpret using a calibrated putty-clay model that suggests large disemployment effects in the longer run. However, our empirical findings here and in DLR (2010) do not suggest sizable employment losses in restaurant sector in the "medium run," i.e., after 12 or 16 quarters following the minimum wage.

Border discontinuity results using QWI data

DLR (2016) also estimates minimum wage elasticities for teen employment using a border discontinuity approach and county-level QWI data from 2000 through 2011. The estimates on earnings are positive, sizable, and statistically significant at the 1 percent level. The estimated teen employment minimum wage elasticity from the two-way fixed effects model is -0.173 and statistically significant at the 1 percent level. In contrast, the estimated employment elasticity with the county-pair period effects falls in magnitude to -0.059 and is statistically indistinguishable from zero. Controlling for time-varying heterogeneity using a border discontinuity design therefore suggests employment effects for teens that are substantially smaller than the two-way fixed-effects model.

DLR (2016) also finds a sizable reduction in turnover following a minimum wage increase: the turnover elasticity is -0.204 when county-pair period effects are included. Importantly, in conjunction with the strong earnings effects, the turnover findings undermine NSW's claim that this research design throws away too much information to detect any effects of the policy on outcomes.

Slichter (2016), who employs a neighboring county discontinuity design, reinforces these conclusions. Slichter relaxes the assumption that differences between nearby counties fully eliminate unobservable factors confounded with minimum wage differences. By using untreated neighbors of minimum wage-raising counties, along with additional control groups of neighbors-of-neighbors of treated counties, etc., Slichter can identify minimum wage effects even when neighboring counties are imperfect controls for one another. This "selection ratio" based refinement of the border approach produces small employment elasticities for teens that are