Spend Down Analysis

Joe Mienko

Sources of Data

The data in this analysis draw from the FamLink data warehouse (FLDW) managed by the Department of Children Youth and Families (DCYF). These data are made available to the author under a data sharing agreement between DCYF and the University of Washington School of Social Work. As of the date of this writing, this analysis is still being reviewed by DCYF.

Population of Interest

We begin our analysis by establishing a population of placement episodes which is ostensibly court involved. This is accomplished by examining the most recent legal status of a given case (`tx_lgl_stat`), the discharge type (`tx_dsch_rsn`), and a series of checks back to the `LEGAL` datamart of the FLDW (as represented by the `fl_dep_exist` flag). Wherever possible, all records in this analysis make use of the "base reporting tables" developed by the business intelligence team at DCYF. As can be seen, we are limiting this analysis to the counties of Grant and Lewis - the two "treatment" counties for the legal representation pilot. We also restrict the sample to children who were under the age of 18 at the point of removal.

```
if object_id('tempdb..##court_episodes') is not null
    drop table ##court_episodes;

select distinct
    rp.latest_removal_dt
  ,id_removal_episode_fact
  ,rp.child
  ,case
    when ljd.cd_jurisdiction = 9
    then 'Douglas'
    else rp.tx_county
  end tx_county_mod
  ,rp.discharge_dt
  ,rp.id_case
  ,case
    when lf_dt is not null
    then lf_dt
  else discharge_dt
end discharge_from_pilot
into ##court_episodes
from base.rptPlacement rp
  left join dbo.legal_fact lf
    on lf.id_case = rp.id_case
  left join dbo.legal_jurisdiction_dim ljd
    on lf.id_legal_jurisdiction_dim = ljd.id_legal_jurisdiction_dim
where (rp.tx_county in ('Grant', 'Lewis', 'Whatcom')
    or ljd.cd_jurisdiction = 9)
  and dbo.fnc_datediff_yrs(birthdate, removal_dt) < 18
  and (tx_lgl_stat in
  ('Closed - Adoption'
```

```
  ,'Closed - Dependency Guardianship No Supv'
  ,'Closed - Superior Court Guardianship'
  ,'Closed - Title 13 Guardianship'
  ,'Closed -Non-parental (3rd party) custody'
  ,'Dependency Guardianship'
  ,'Dependent'
  ,'Dependent - Legally Free'
  ,'EFC Dependent'
  ,'Non-parental (3rd Party) custody'
  ,'Parental Custody -Continued Court Action'
  ,'Protective Custody'
  ,'Shelter Care'
  ,'Superior Court Guardianship')
  or tx_dsch_rsn = 'Returned to Custody of Parents - Dependency Dismissed'
  or fl_dep_exist = 1)
```

Expected Time to Permanency

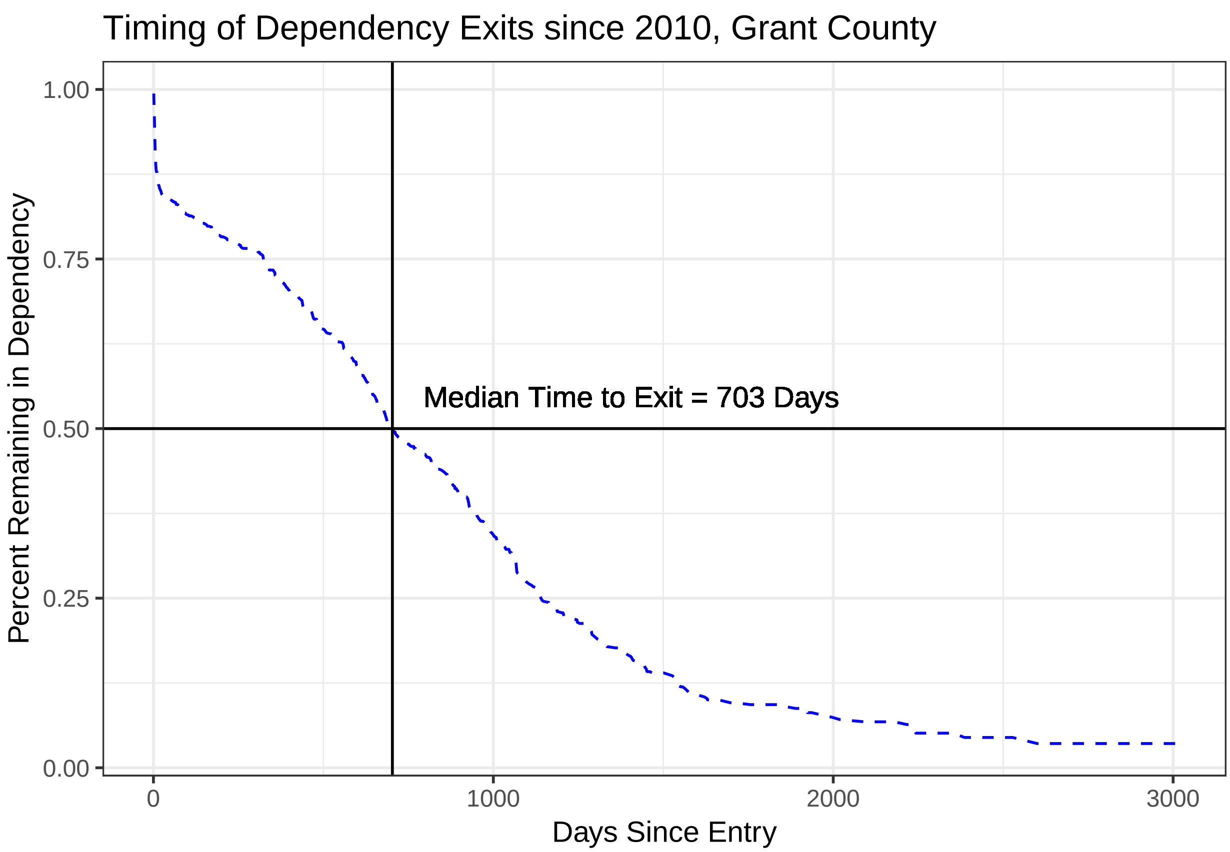
A critical component of this analysis concerns our expectations for the timing of permanency outcomes in the Counties of Grant and Lewis (the "treatment counties") and Whatcom and Douglas (the "control counties"). There are a number of methods for making such estimates. However, in order to make use of the most recent data available for this analysis, we will employ a Kaplan-Meier estimator as implemented within the `survival` package by Terry M. Therneau and Patricia M. Grambsch (2000). This is accomplished by establishing subsetting the temporary table defined above into a standard event-history table.

```
with surv_prep as
(
select
  rp.child id_prsn_child
  ,rp.latest_removal_dt
  ,iif(rp.discharge_from_pilot = '9999-12-31', '2018-04-27', rp.discharge_from_pilot) discharge_dt
  ,iif(rp.discharge_from_pilot = '9999-12-31', null
    , rp.discharge_from_pilot) discharge_dt_null
  ,iif(rp.discharge_from_pilot = '9999-12-31', 0, 1) fl_discharge
,datediff(dd, rp.latest_removal_dt,
  iif(rp.discharge_dt = '9999-12-31', '2018-04-27'
    , rp.discharge_from_pilot)) + 1 los
  ,rp.id_case
  ,rp.tx_county_mod
from ##court_episodes rp
where rp.latest_removal_dt between '2010-01-01' and '2018-04-27'
)
select * from surv_prep where los >= 1
```

The survival curves generated from the `survival` package are plotted below.

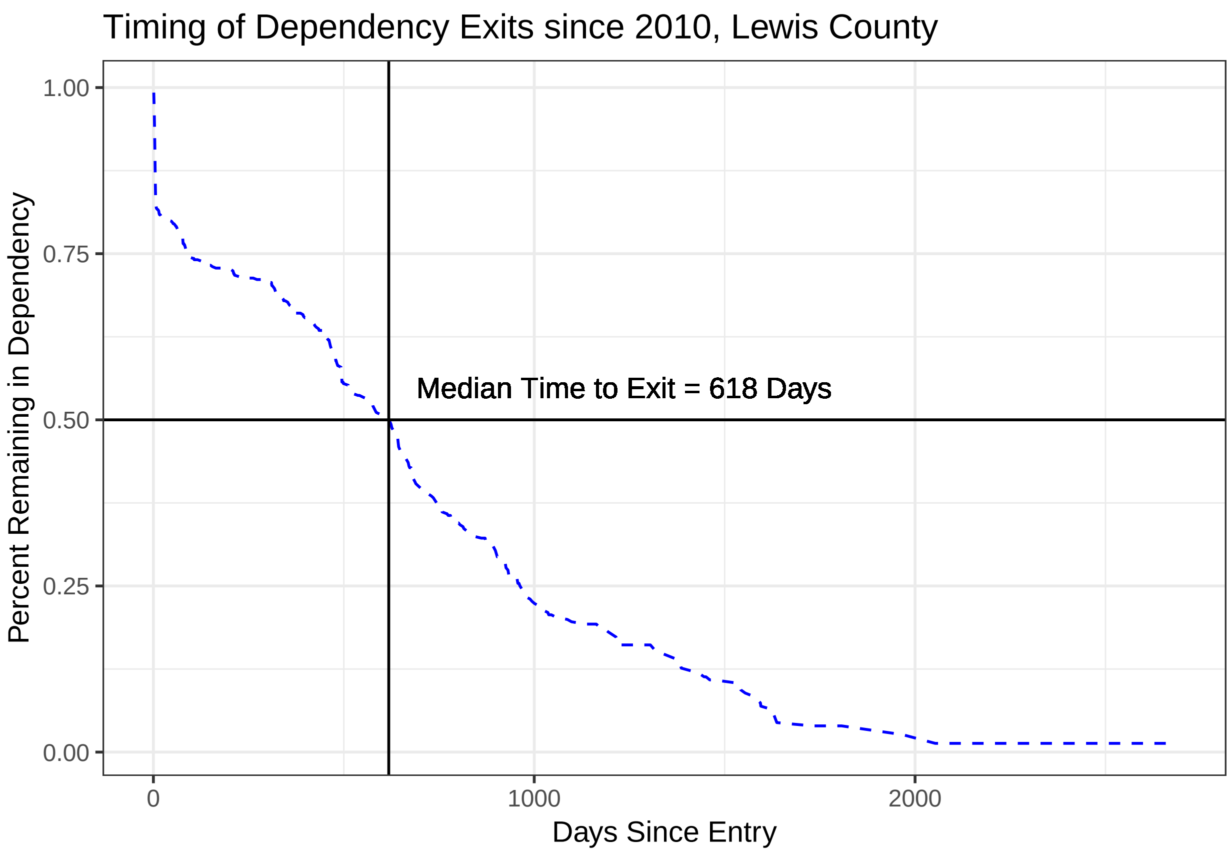
```
historical_surv_grant <- read_feather("historical_surv_grant.feather")

median_loc_grant <- which.min(abs(historical_surv_grant$surv - .5))
median_value_grant <- historical_surv_grant$surv[median_loc_grant]
median_days_grant <- historical_surv_grant$time[median_loc_grant]
median_label_grant <- paste0("Median Time to Exit = "
```

```r
                              ,median_days_grant
                              ," Days")


ggplot(historical_surv_grant
       ,aes(y = surv
            ,x = time)) +
  geom_line(colour = "blue", linetype = "dashed") +
  ggplot2::geom_vline(xintercept = median_days_grant) +
  ggplot2::geom_hline(yintercept = round(median_value_grant, 2)) +
  geom_text(aes(median_days_grant*2
                ,median_value_grant
                ,label = median_label_grant
                ,vjust = -1)) +
  ylab("Percent Remaining in Dependency") +
  xlab("Days Since Entry") +
  ggtitle("Timing of Dependency Exits since 2010, Grant County") +
  theme_bw()
```



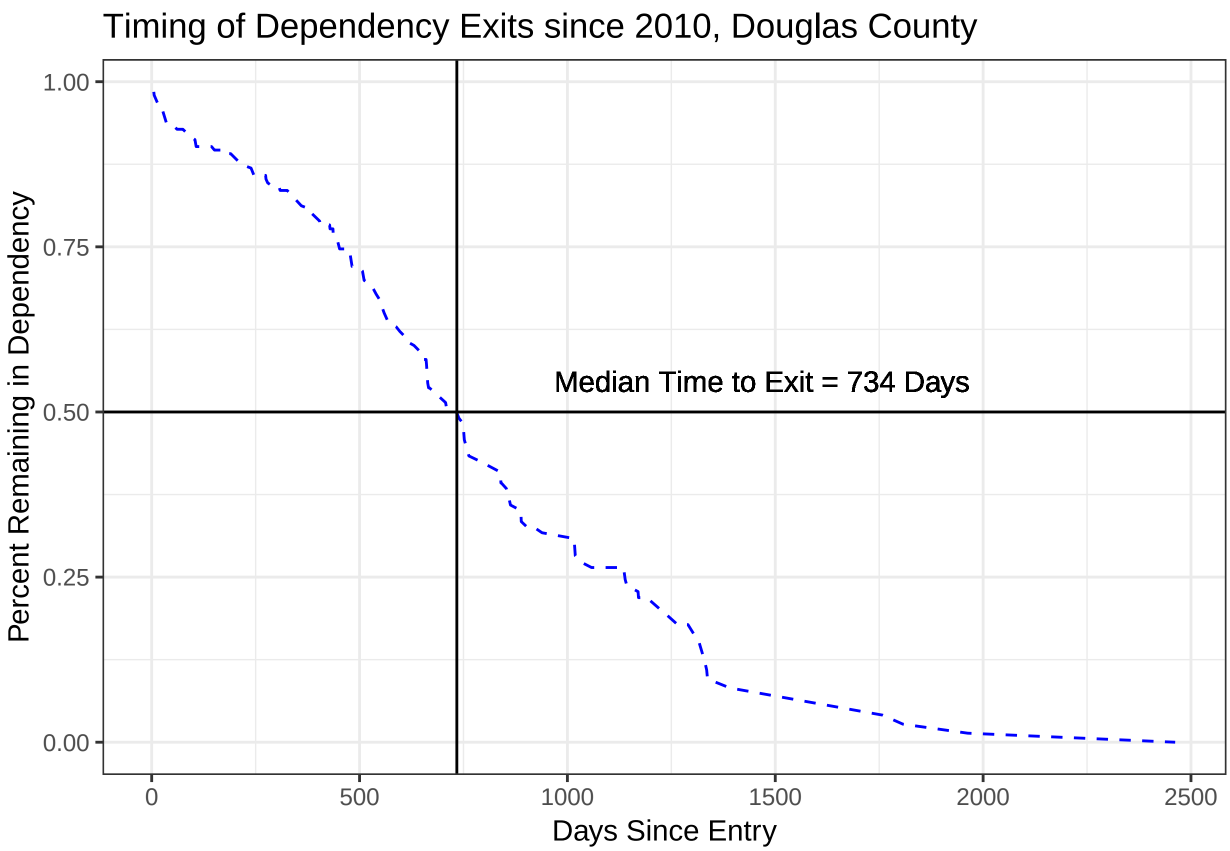

```r
historical_surv_lewis <- read_feather("historical_surv_lewis.feather")

median_loc_lewis <- which.min(abs(historical_surv_lewis$surv - .5))
median_value_lewis <- historical_surv_lewis$surv[median_loc_lewis]
median_days_lewis <- historical_surv_lewis$time[median_loc_lewis]
median_label_lewis <- paste0("Median Time to Exit = "
                             ,median_days_lewis
                             ," Days")
```

```r
ggplot(historical_surv_lewis
       ,aes(y = surv
            ,x = time)) +
  geom_line(colour = "blue", linetype = "dashed") +
  ggplot2::geom_vline(xintercept = median_days_lewis) +
  ggplot2::geom_hline(yintercept = round(median_value_lewis, 2)) +
  geom_text(aes(median_days_lewis*2
                ,median_value_lewis
                ,label = median_label_lewis
                ,vjust = -1)) +
  ylab("Percent Remaining in Dependency") +
  xlab("Days Since Entry") +
  ggtitle("Timing of Dependency Exits since 2010, Lewis County") +
  theme_bw()
```



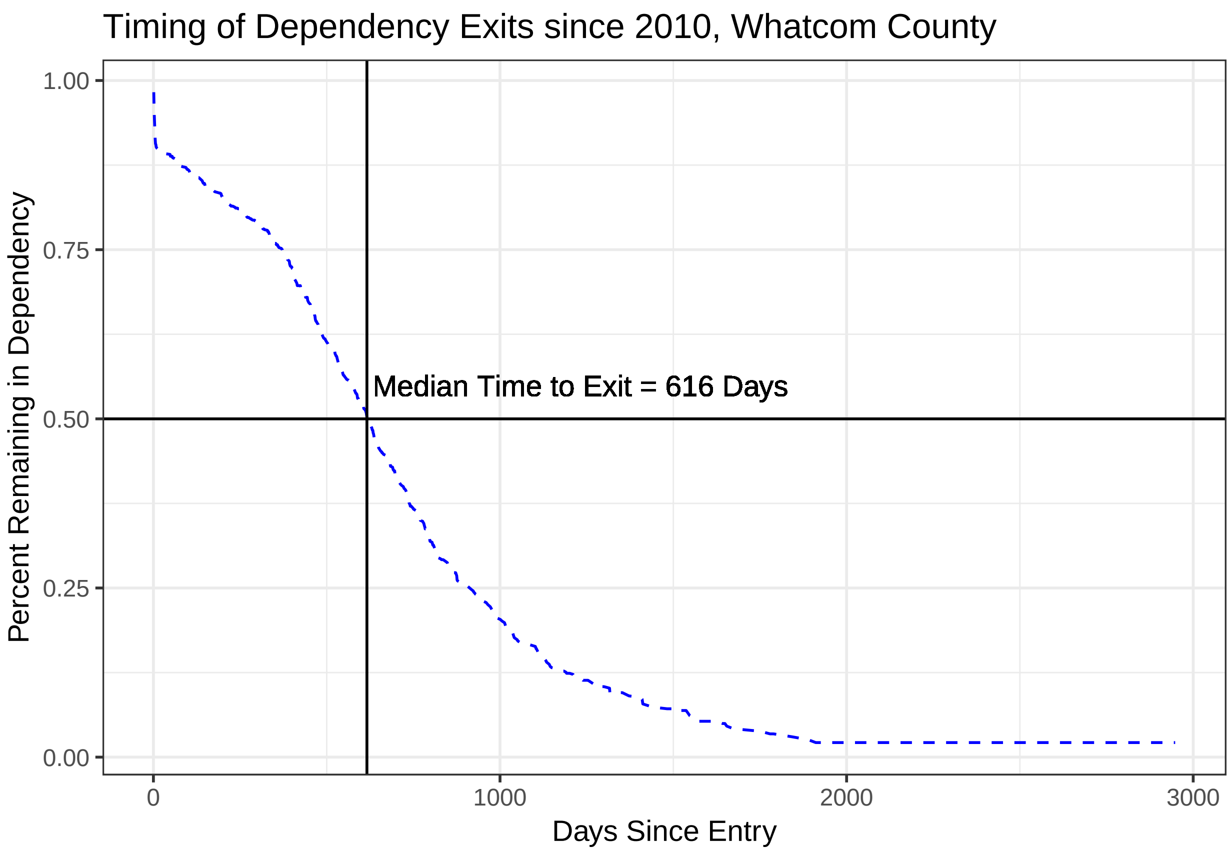

```r
historical_surv_douglas <- read_feather("historical_surv_douglas.feather")

median_loc_douglas <- which.min(abs(historical_surv_douglas$surv - .5))
median_value_douglas <- historical_surv_douglas$surv[median_loc_douglas]
median_days_douglas <- historical_surv_douglas$time[median_loc_douglas]
median_label_douglas <- paste0("Median Time to Exit = "
                               ,median_days_douglas
                               ," Days")

ggplot(historical_surv_douglas
       ,aes(y = surv
```

```
             ,x = time)) +
  geom_line(colour = "blue", linetype = "dashed") +
  ggplot2::geom_vline(xintercept = median_days_douglas) +
  ggplot2::geom_hline(yintercept = round(median_value_douglas, 2)) +
  geom_text(aes(median_days_douglas*2
                ,median_value_douglas
                ,label = median_label_douglas
                ,vjust = -1)) +
  ylab("Percent Remaining in Dependency") +
  xlab("Days Since Entry") +
  ggtitle("Timing of Dependency Exits since 2010, Douglas County") +
  theme_bw()
```




```
historical_surv_whatcom <- read_feather("historical_surv_whatcom.feather")

median_loc_whatcom <- which.min(abs(historical_surv_whatcom$surv - .5))
median_value_whatcom <- historical_surv_whatcom$surv[median_loc_whatcom]
median_days_whatcom <- historical_surv_whatcom$time[median_loc_whatcom]
median_label_whatcom <- paste0("Median Time to Exit = "
                               ,median_days_whatcom
                               ," Days")

ggplot(historical_surv_whatcom
       ,aes(y = surv
            ,x = time)) +
  geom_line(colour = "blue", linetype = "dashed") +
  ggplot2::geom_vline(xintercept = median_days_whatcom) +
```

```
ggplot2::geom_hline(yintercept = round(median_value_whatcom, 2)) +
geom_text(aes(median_days_whatcom*2
              ,median_value_whatcom
              ,label = median_label_whatcom
              ,vjust = -1)) +
ylab("Percent Remaining in Dependency") +
xlab("Days Since Entry") +
ggtitle("Timing of Dependency Exits since 2010, Whatcom County") +
theme_bw()
```



As can be seen, the median time to exit for both Grant and Lewis is nearly two years (703 days and 618 days respectively). In other words, this is the number of days it takes for half of a "typical" cohort of dependent children to exit from the system. The median for Douglas and Whatcom is 734 days and 616 days respectively.

This is, however, only one point on the estimated survival function for each county. In the following sections, we will make use of the entire estimated function for each jurisdiction.

Historical Daily Counts and Flows of Dependent Children

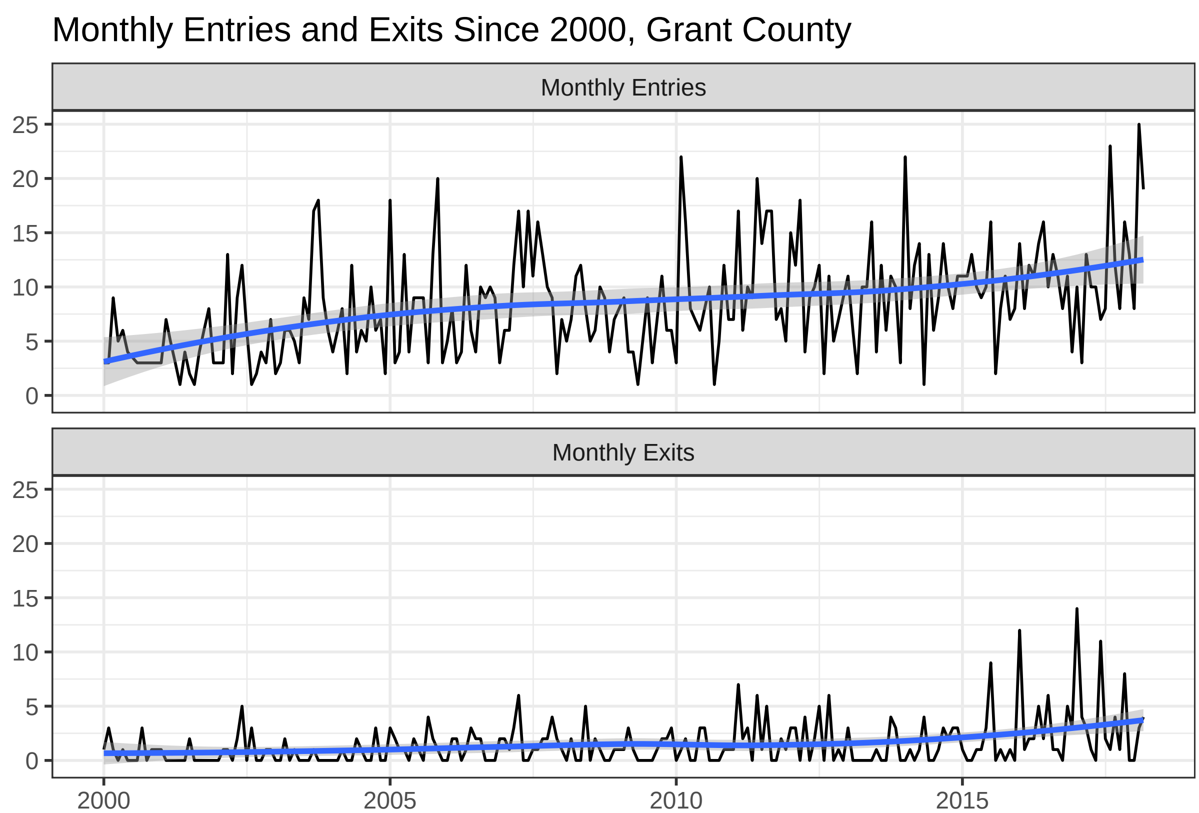
The previous section can provide us with good information regarding how long we might expect children in the pilot counties to remain in care once they have entered. In order to determine how long the pilot should plan to serve the children on its caseload, it will also be useful for us to understand the rate at which children enter and exit care in these counties.

The next chunk of code selects information (using the same temporary table as a starting point) concerning the monthly counts of entries and exits into dependency for each county.

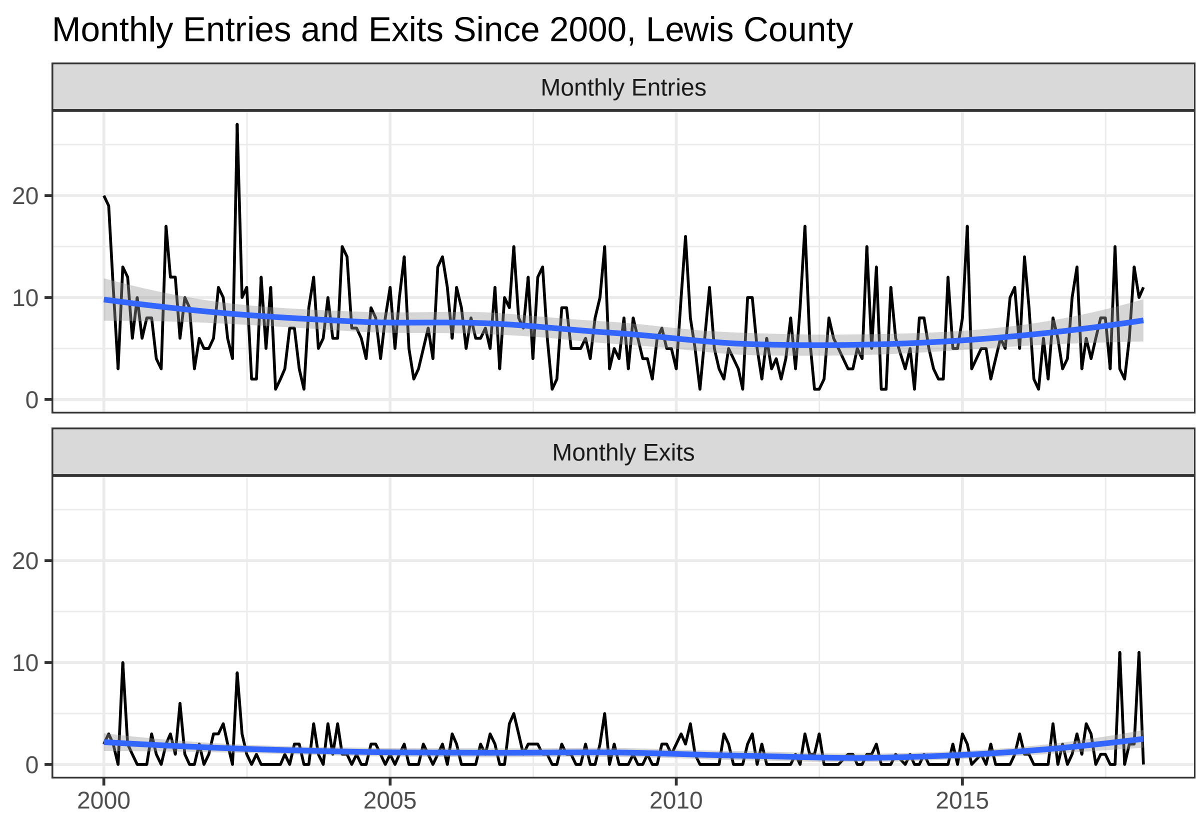
```sql
with calendar_dates as
(
select
  cd.*
  ,case
    when cty.i = 1
    then 'Lewis'
    when cty.i = 2
    then 'Grant'
    when cty.i = 3
    then 'Douglas'
    when cty.i = 4
    then 'Whatcom'
    else null
  end tx_county_mod
from calendar_dim cd, dbo.NumbersTable(1, 4, 1) cty
where cd.calendar_date between '2000-01-01' and '2018-04-27'
), placements as
(
select
  rp.latest_removal_dt
  ,id_removal_episode_fact
  ,iif(rp.discharge_from_pilot = '9999-12-31'
  , '2018-04-27', rp.discharge_from_pilot) discharge_dt
  ,iif(rp.discharge_from_pilot = '9999-12-31'
  , null, rp.discharge_from_pilot) discharge_dt_null
  ,rp.tx_county_mod
from ##court_episodes rp
), inflow_counts as
(
select distinct
  calendar_date
  ,p.tx_county_mod
  ,count(distinct id_removal_episode_fact) inflow_of_placements
from calendar_dates cd
  left join placements p
    on cd.calendar_date = latest_removal_dt
    and cd.tx_county_mod = p.tx_county_mod
group by
  calendar_date
  ,p.tx_county_mod
), outflow_counts as
(
select distinct
  calendar_date
  ,p.tx_county_mod
  ,count(distinct id_removal_episode_fact) outflow_of_placements
from calendar_dates cd
  left join placements p
    on cd.calendar_date = discharge_dt_null
    and cd.tx_county_mod = p.tx_county_mod
group by
  calendar_date
```

```
  ,p.tx_county_mod
), daily_counts as
(
select distinct
  ic.calendar_date
  ,ic.tx_county_mod
  ,isnull(ic.inflow_of_placements, 0) total_inflow_of_placements
  ,isnull(oc.outflow_of_placements, 0) total_outflow_of_placements
from inflow_counts ic
  left join outflow_counts oc
    on ic.calendar_date = oc.calendar_date
    and ic.tx_county_mod = oc.tx_county_mod
)

select
  sum(dc.total_inflow_of_placements) total_inflow_of_placements
  ,sum(dc.total_outflow_of_placements) total_outflow_of_placements
  ,cd.month
  ,cd.tx_county_mod
from calendar_dates cd
  join daily_counts dc
    on cd.calendar_date = dc.calendar_date
    and cd.tx_county_mod = dc.tx_county_mod
where cd.month < '2018-04-01'
group by
  cd.month
  ,cd.tx_county_mod
```

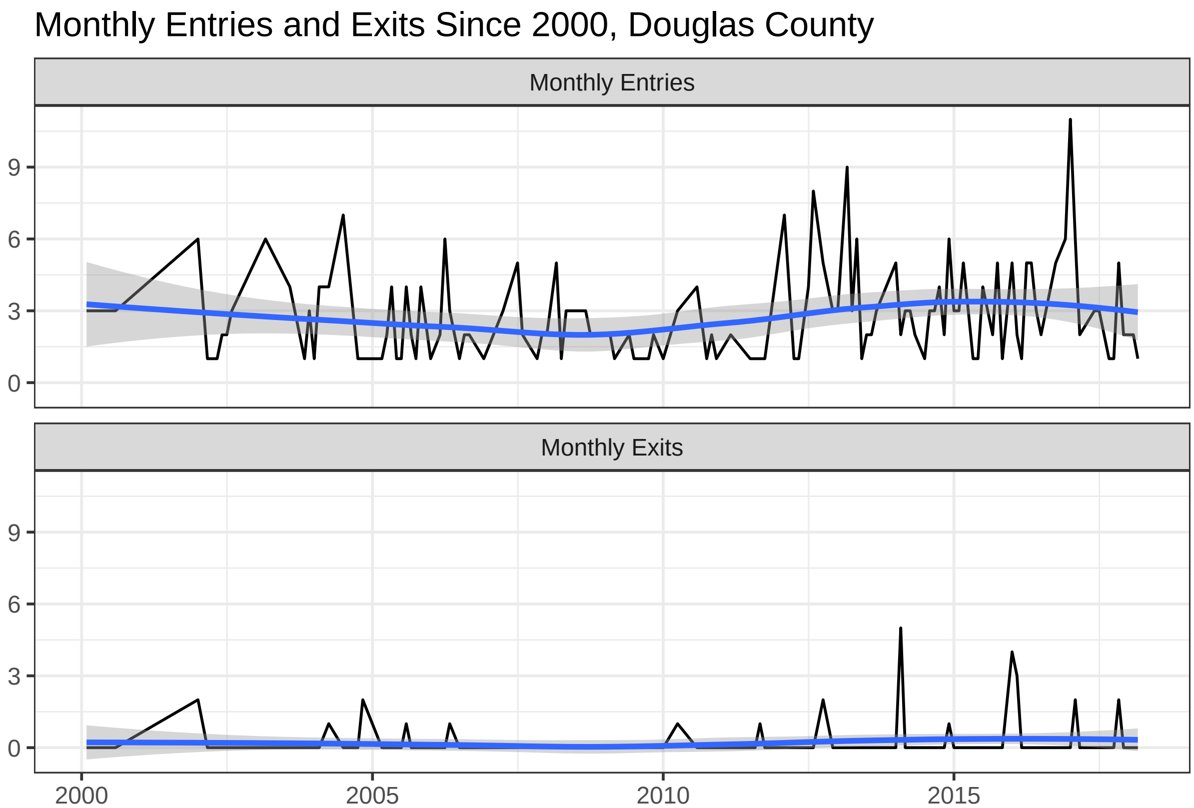
```
dat_stock_and_flow <- read_feather("dat_stock_and_flow.feather")

flow_names <- list(
  "total_inflow_of_placements"="Monthly Entries",
  "total_outflow_of_placements"="Monthly Exits"
)

flow_labeller <- function(variable,value){
  return(flow_names[value])
}

dat_stock_and_flow %>%
  filter(tx_county_mod == "Grant") %>%
  select(-tx_county_mod) %>%
  gather(key = measure, value = count, -month) %>%
  ggplot(aes(y = count, x = month)) +
  geom_line() +
  geom_smooth() +
  facet_wrap(.~measure
             ,nrow = 2
             ,labeller = flow_labeller) +
  xlab("") +
  ylab("") +
  ggtitle("Monthly Entries and Exits Since 2000, Grant County") +
  theme_bw()
```



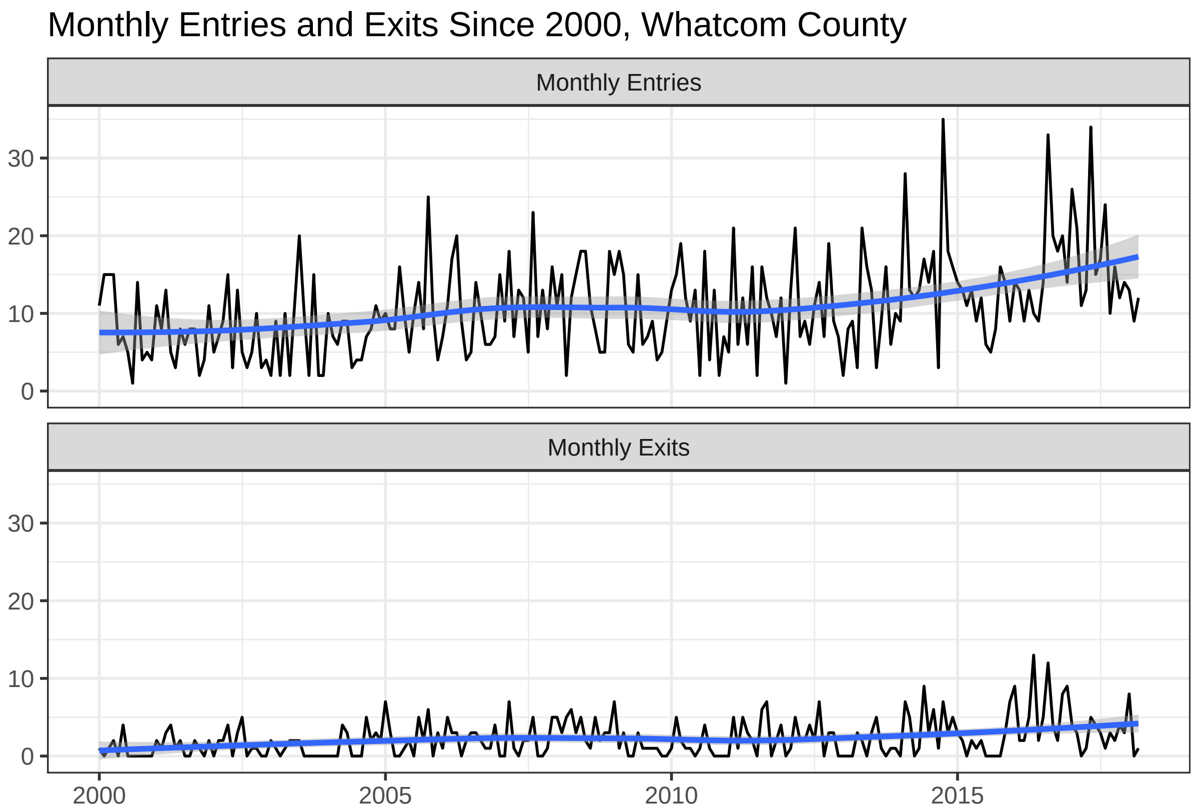

```
dat_stock_and_flow %>%
  filter(tx_county_mod == "Lewis") %>%
  select(-tx_county_mod) %>%
  gather(key = measure, value = count, -month) %>%
  ggplot(aes(y = count, x = month)) +
  geom_line() +
  geom_smooth() +
  facet_wrap(.~measure
             ,nrow = 2
             ,labeller = flow_labeller) +
  xlab("") +
  ylab("") +
  ggtitle("Monthly Entries and Exits Since 2000, Lewis County") +
  theme_bw()
```




```
dat_stock_and_flow %>%
  filter(tx_county_mod == "Douglas") %>%
  select(-tx_county_mod) %>%
  gather(key = measure, value = count, -month) %>%
  ggplot(aes(y = count, x = month)) +
  geom_line() +
  geom_smooth() +
  facet_wrap(.~measure
             ,nrow = 2
             ,labeller = flow_labeller) +
  xlab("") +
  ylab("") +
  ggtitle("Monthly Entries and Exits Since 2000, Douglas County") +
  theme_bw()
```




```
dat_stock_and_flow %>%
  filter(tx_county_mod == "Whatcom") %>%
  select(-tx_county_mod) %>%
  gather(key = measure, value = count, -month) %>%
  ggplot(aes(y = count, x = month)) +
  geom_line() +
  geom_smooth() +
  facet_wrap(.~measure
              ,nrow = 2
              ,labeller = flow_labeller) +
  xlab("") +
  ylab("") +
  ggtitle("Monthly Entries and Exits Since 2000, Whatcom County") +
  theme_bw()
```



This historical information can be used in a variety of ways. For our current purposes, we want to make a reasonable estimate as to how many entries and exits can be expected for several months into the future. While a complete discussion of the forecasting models is beyond the scope of this analysis, we will proceed with a generalization of moving average models referred to as autoregressive integrated moving average (ARIMA) models, as implemented by Hyndman et al. (2018). Specifically, we will make use of a non-seasonal ARIMA(p,d,q) model in which p is defined as the number of time lags in the model (i.e. how far back the model looks for information), d is the number of times the have had past values subtracted (typically for stablization), and q is the order of the underlying moving-average model. In order to make use of this form of ARIMA, we will first "deseasonalize" our data. In other words, we will identify any patterns of seasonality in the data, and focus our analysis on the underlying trend of the data. We will then follow the "automatic ARIMA" algorithm developed by Hyndman, Khandakar, and others (2007) to obtain reasonable starting points for p, d, and q above. Using visual examination of the residuals generated from these parameters, we initially adjusted the q parameter. Due to little effect resulting from these adjustments (and little theoretical justification), we ultimately just select the "automati ARIMA" parameters.

To be clear, we do not propose the selected ARIMA models to be recommended forecasting models beyond this analysis. Here, the chosen models are being selected as reasonable estimates - preferrable to simply averaging entries and exits over the observed time period.

References

Hyndman, Rob J, George Athanasopoulos, Christoph Bergmeir, Gabriel Caceres, Leanne Chhay, Mitchell O'Hara-Wild, Fotios Petropoulos, Slava Razbash, Earo Wang, and Farah Yasmeen. 2018. "Forecast: Forecasting Functions for Time Series and Linear Models."

Hyndman, Rob J, Yeasmin Khandakar, and others. 2007. *Automatic Time Series for Forecasting: The Forecast Package for R*. 6/07. Monash University, Department of Econometrics; Business Statistics.

Terry M. Therneau, and Patricia M. Grambsch. 2000. *Modeling Survival Data: Extending the Cox Model*.

New York: Springer.